Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Characterizing the interruption-recovery patterns of urban air pollution under the COVID-19 lockdown in China

Wan-Jin Cai \(^{a}\), Hong-Wei Wang \(^{a}\), Cui-Lin Wu \(^{a}\), Kai-Fa Lu \(^{b}\), Zhong-Ren Peng \(^{b, *}\), Hong-Di He \(^{a}\)

\(^{a}\) Center for Intelligent Transportation Systems and Unmanned Aerial Systems Applications Research, State-Key Laboratory of Ocean Engineering, School of Naval Architecture, Ocean and Civil Engineering, Shanghai Jiao Tong University, Shanghai, 200240, China

\(^{b}\) International Center for Adaptation Planning and Design, College of Design, Construction and Planning, University of Florida, PO Box 115706, Gainesville, FL, 32611-5706, USA

**ARTICLE INFO**

**Keywords:**
- COVID-19
- Interruption-recovery
- Urban lockdown policy
- Air pollution
- Regression discontinuity design

**ABSTRACT**

The COVID-19 pandemic provides an opportunity to study the effects of urban lockdown policies on the variation in pollutant concentrations and to characterize the recovery patterns of urban air pollution under the interruption of COVID-19 lockdown policies. In this paper, interruption-recovery models and regression discontinuity design were developed to characterize air pollution interruption-recovery patterns and analyze environmental impacts of the COVID-19 lockdown, using air pollution data from four Chinese metropolises (i.e., Shanghai, Wuhan, Tianjin, and Guangzhou). The results revealed the air pollutant interruption-recovery curve represented by the three lockdown response periods (Level I, Level II and Level III) during COVID-19. The curve decreased during Level I (25.3\%–48.8\% drop in the concentration of NO\(_2\) has been observed in the four metropolises compared with the same period in 2018–2019.), then recovered around reopening, but decreased again during Level III. Moreover, the interruption-recovery curve of the year-on-year air pollution difference suggests a process of first decreasing during Level I and gradually recovering to a new equilibrium during Level III (e.g., the unit cumulative difference of NO\(_2\) mass concentrations in Shanghai was 21.7, 22.5, 11.3 (\(\mu\)g/m\(^3\)) during Level I, II, and III and other metropolises shared similar results). Our findings reveal general trends in the air quality externality of different lockdown policies, hence could provide valuable insights into air pollutant interruption-recovery patterns and clear scientific guides for policymakers to estimate the effect of different lockdown policies on urban air quality.

1. Introduction

The outbreak of the Corona Virus Disease 2019 (COVID-19) pandemic has detrimentally impacted urban development and human health. Confirmed cases of the new coronavirus reached nearly 79 million worldwide, with 1.7 million deaths, by the end of 2020 \([\text{WHO}_2020]\). To curb the spread of COVID-19, lockdown policies varying in degree were implemented across cities in China and urban traffic and industrial production were strictly limited. Nonetheless, this response also provides an opportunity to characterize the urban air pollution recovery pattern under the interruption of pandemic lockdown policies. Additionally, the response can isolate the major pollution sources, which makes it the best natural experiment for assessing the impact of lockdown policies. The concept of ‘interruption-recovery’ is introduced here that has been commonly used to describe the process of a system to revert, or ‘bounce back’ to a normal level after its original state has been affected by a disruptive event. To our knowledge, existing research rarely focuses on the interruption-recovery pattern of urban air pollution during COVID-19. A good characterization of such interruption-recovery patterns not only can often assist policymakers in better understanding the dynamics of urban air pollution and has potential for supporting decision-making of lockdown policies \([1–4]\), but may also uncover predictable trends in the variation of urban air quality that could be useful in case that similar events were to happen again. Therefore, it is important to understand and evaluate the air pollution interruption-recovery patterns and to analyze the differential impact of various lockdown policies on urban air quality during the COVID-19 pandemic.

As reported in previous studies, the emergence and fast spread of COVID-19 has significantly improved urban air quality compared with
the same period in years before, and the concentrations of regulatory air pollutants (for example NO\textsubscript{x}, SO\textsubscript{2}, PM\textsubscript{2.5}, PM\textsubscript{10}, CO) in urban areas have also declined substantially [5–8], particularly those of PM\textsubscript{10} and NO\textsubscript{2} due to sharp declines in traffic volume [9]. The lowered PM\textsubscript{2.5}, SO\textsubscript{2}, and CO concentrations were mainly caused by the shutdown of the industrial sector [10]. By contrast, the O\textsubscript{3} concentrations across China’s megacities show a trend of increase under the impact of COVID-19 [5,11,12]. Most states governments in the US issued lockdown in March 2020, which led to almost all mass transportation and industrial activities prohibited. Hence, ground-based observations around US densely populated areas like California and New York showed a significant drop in the concentration of NO\textsubscript{2} during the first phase of the lockdown [13,14]. Reduction of traffic volume during the pandemic was effective in improving air quality in these areas. Except for vehicular emissions, the change in air pollution can still be attributed to the role of other sources such as residential emissions, power generation, or secondary PM [13,15]. A sharp decrease in the concentration of CO, SO\textsubscript{2}, PM\textsubscript{2.5}, and an increase of O\textsubscript{3} has been observed in most US monitoring stations as well [16–19]. Research focusing on South Asia critically investigated lockdown effects toward concentrations of air pollutants and found that a significant reduction of air quality index (AQI) was observed over most polluted ranked cities like Delhi, Dhaka, Kathmandu, Colombo due to the total shutdown [20–24]. Similar results have also been found at the all-countries level [25] such as Australia [26], UK [27], Italy [28], Spain [29], and Brazil [30]. Above all, existing research mainly focuses on the air pollution change during the earlier stage of the COVID-19. However, studies conducted to clearly reveal the interruption-recovery pattern of urban air pollution for the entire period of COVID-19 lockdown policies are limited in number [6,31]. In this study, the air pollution interruption-recovery patterns have been revealed and can provide clear scientific guides for policymakers to estimate the effect of different lockdown policies on urban air quality.

In China, the pandemic response measures span different urban lockdown policies at Level I, Level II, and Level III. Fig. 1 presents the detailed timelines of different lockdown policies implemented in the four megacities. Table 1 shows the detailed urban lockdown policies during different response stages (i.e., Level I, Level II, and Level III). Accordingly, this study focuses on revealing the dynamics of urban air pollution spanning from Level I to Level III, corresponding to different urban lockdown policies.

Generally, one typical interruption-recovery pattern is composed of a loss process coming from the interruption and a recovery process till a new equilibrium [2,32–34]. Here, we hypothesize that the urban air pollution level diminished significantly going from Level I to Level II, and then gradually recovered to a new equilibrium state. Basic and extended air pollution interruption-recovery patterns are shown in Fig. 2 (a). Fig. 2(b) and (c) are the patterns found in the paper and will be further discussed later in Section 3.

To determine and distinguish the interruption-recovery patterns, it is essential to evaluate the actual effects of different lockdown policies under COVID-19 upon urban air quality [35]. quantified the heterogeneous effects of COVID-19 lockdown measures on air quality via difference-in-differences (DID) that can account for uncontrollable and unpredictable factors, and then adopted an instrument variable (IV), which helps alleviate the omitted variable bias, to evaluate pollution’s adverse impact on health after estimating the effect of traffic control upon pollution. These statistical methods are quasi-experimental methodologies that are used to eliminate confounding factors and estimate causal relationships when controlled experiments are infeasible. However, these methodologies may still be subject to certain biases; for example an omitted variable bias for DID and endogeneity problems for IV [36–38]. Hence, the regression discontinuity design (RDD) models have been broadly applied to analyze the effectiveness of urban policies in both social and environmental research fields [39,40]. Nonetheless, the RDD is also a quasi-experimental methodology that can estimate the causal impact of an intervention upon variation in the independent variables. Additionally, compared with DID and IV, RDD is more closely related to randomized experiments and with higher accuracy and reliability [37,41]. Therefore, in this study, the RDD model was adopted to judge whether lockdown policies exerted an influence on urban air pollution.

In this paper, we aimed to characterize and evaluate the interruption-recovery patterns of urban air pollution in four Chinese megacities and to further analyze the impacts of different lockdown policies on urban air quality under the COVID-19 pandemic, using air pollutant data from national environmental monitoring stations across Shanghai, Wuhan, Tianjin, and Guangzhou. Additionally, an RDD model was developed to quantify the air quality impacts accompanying different lockdown policies and to investigate the variation in the air pollution level under the COVID-19 lockdown. To achieve this goal: (1) We selected four typical megacities that encompassed multiple policy categories and air pollution interruption-recovery patterns, being separately located in Eastern, Northern, Southern, and Central China. The four megacities (i.e., Shanghai, Guangzhou, Tianjin, and Wuhan) were fully shut down for 2, 1, 3, and 3 months, respectively. (2) Based on the periods of Level I, Level II, and Level III, the corresponding air pollutant data in 2018 and 2019 were extracted to evaluate changes in urban air quality under different lockdown policies. (3) The data-driven comparative analysis and RDD model were both adopted to characterize and evaluate interruption-recovery patterns of air pollution across the four megacities under the COVID-19 lockdown.

2. Methods and data

In this section, the details of the data set are first described. Then, we introduce the methodology of regression discontinuity design (RDD) and a test for the robustness of this RDD model. We conclude this section by presenting how to calculate the loss of performance (LoP).

2.1. Data description

The study area encompasses four megacities having high population densities in China, namely Shanghai, Tianjin, Guangzhou, and Wuhan. Based on data released by the National Health Commission, a total of 87 052 confirmed cases of COVID-19 nationwide occurred in 2020, of which ca. 58% were in Wuhan alone. These four megacities are

| Table 1 The pandemic urban lockdown policies at different response stages (Level I, Level II, and Level III). |
| --- |
| **Response stages** | **Urban lockdown policies** |
| Level I | ◆ People were compulsorily required to stay at home unless they needed to purchase daily necessities or travel for urgent purposes. ◆ After March 10, 2020, enterprises could reopen if anti-epidemic requirements were met. |
| Level II | ◆ Intercity travel across domestic cities was allowed so long as people wore masks. |
| Level III | ◆ Most public facilities reopened and some public events were held under strict management and conditions. |

Fig. 1. Timeline and lockdown levels of the four megacities’ response against COVID-19.
separately located in East, North, South, and Central China. The portion of the study area corresponding to Shanghai covers 120°97′E–121°70′E and 31°09′N–31°30′N; likewise, that for Tianjin is 117°14′E–117°76′E and 38°83′N–39°21′N, for Guangzhou it is 113°21′E–113°58′E and 22°48′N–23°55′N, and Wuhan it is 113°85′E–114°42′E and 30°29′N–31°78′N. Hourly data of air quality index (AQI) and six regulatory air pollutants—NO₂, PM₂.₅, PM₁₀, SO₂, CO, and O₃—were extracted from air quality monitoring stations of China National Environmental Monitoring Center in the four megacities from January 1, 2020 to August 31, 2020, and again in the same period in the prior two years (i.e., 2018 and 2019). Additionally, the roadside traffic-related air pollutant data were acquired from the Shanghai Environmental Protection Bureau. Hence, this data set on urban air pollutants entails spatiotemporal characteristics of air quality in the four megacities.

Meteorological conditions including air temperature, wind direction, and wind speed, among others, are known to greatly impact urban air pollutants’ level via physical and chemical processes, such as accumulation or dispersion and multiphase reactions for aerosol formation and growth [9,42–44]. It is therefore reasonable to suppose that changes in urban air pollutant concentrations during the COVID-19 lockdown may partially depend on meteorological conditions during that period. To account for this influence from meteorological conditions, hourly meteorological data (i.e., air temperature, wind direction, and wind speed) during the same period per year were obtained from the National Climate Data Center (NCDC), for recordings made at the Tianjin Binhai International Airport, Shanghai Hongqiao International Airport, Guangzhou Baiyun International Airport, and Wuhan Tianhe International Airport.

Fig. 3 shows the geographical locations and wind rose diagrams of
of pollutant mass concentration on day $t$, used here to account for the potential serial correlation in the time-series data analysis; $f(mf_t)$ is the nonlinear function of meteorological factors including air temperature, wind direction, and wind speed; $\epsilon_t$ is the error term, also the auto-correlated term on day $t$.

2.2.2. Robustness test of the RDD model

After developing the RDD model, a robustness test is needed to verify the model’s results. As revealed by previous studies, a robustness test could verify the causality among factors derived from RDD and the validity of the RDD model by considering the support obtainable from these three tests [51]:

(1) Covariate continuity test: This is also called the pseudo-outcome test. Specifically, covariates (i.e., meteorological factors) are used as pseudo-outcomes to test whether the corresponding RDD estimates are significant. If the estimates are indeed significant, the covariates violate the continuity assumption.

(2) Test for continuity of reference variable distribution: If the reference variable conforms to a continuous distribution, an individual variable cannot accurately manipulate the reference variable at the cutoff.

(3) Pseudo-cutoff point test: In other positions of the reference variable (e.g., the midpoints on the left and right side of the cutoff, as pseudo-cutoffs), the same method is adopted to calculate the RDD estimates. If these pseudo-cutoffs are found significant, the RDD model is not correct, that is under influence of other observational factors; hence, causal effects are mainly driven by other mixed jumps (albeit unobserved) rather than an intervention’s influence per se [40].

2.2.3. Loss of performance (LoP)

In this paper, we defined the cumulative difference of pollutant mass concentrations between the COVID-19 period in 2020 and the same period in the prior years as Loss of Performance (LoP) (see Fig. 4), as shown in Equation (2):

$$\text{LoP}_t = \int_{t_0}^{t} \left| \text{pmc}_{t'} - \text{pmc}_{t_0} \right| dt$$

where, $\text{pmc}_{t}$ is the outcome variable, this being the natural logarithm of pollutant mass concentration, except for CO, from monitoring stations in the four cities on day $t$. $t_0$ is the fixed effect of monitoring stations in each city; the $a_1$, $a_2$, $a_3$, $a_4$ are the coefficients of interest of the policy effects of Level I, Level II, Reopen, and Level III, respectively. $N_t$ is the indicator variable of a given lockdown policy, which equals 1 during the response period and 0 before the response period. $T$ is the time variable, representing the transformation of the normalized time $t$ to be specific, $T$ equals 1 on the first day of the policy implementation and it equals -1 on the last day before the policy implementation, and so on; $\log(\text{pmc}_{t_0})$ is the lag term of pollutant mass concentration.

Table 2

| Name          | Latitude | Longitude | Population (millions) | Temperature (°C) | Wind speed (m/s) | Number of stations |
|---------------|----------|-----------|-----------------------|------------------|------------------|-------------------|
| Shanghai      | 31.41°E  | 121.49°N  | 24.281                | 12.43            | 2.50             | 10                |
| Tianjin       | 39.72°E  | 117.31°N  | 15.618                | 9.66             | 2.90             | 9                 |
| Guangzhou     | 23.16°E  | 113.27°N  | 15.301                | 19.68            | 2.74             | 10                |
| Wuhan         | 30.58°E  | 114.03°N  | 11.212                | 12.31            | 2.54             | 9                 |

Fig. 4. A sketch of loss of performance (LoP).
where, $pmc_t$ is pollutant mass concentration of NO$_2$ (μg/m$^3$), PM$_{2.5}$ (μg/m$^3$), PM$_{10}$ (μg/m$^3$), SO$_2$ (μg/m$^3$), O$_3$ (μg/m$^3$), or CO (mg/m$^3$), on day $t$ during the pandemic in 2020; $pmc_{tr}$ is the pollutant mass concentration on day $t$ during the same time in the prior years; $i$ is a given response stage; $t_{ib}$ is the start date of response stage $i$, and $t_{ie}$ is the end date of response stage $i$.

Finally, Unit LoP, which is LoP divided by the time span, has been defined as shown in Equation (3):

$$
\text{Unit LoP}_i = \frac{\int_{t_{ib}}^{t_{ie}} |pmc_t - pmc_{tr}| dt}{t_{ie} - t_{ib}}
$$

(3)

The concept of LoP can be used to denote the effect of COVID-19 lockdown policies on urban air pollution [52]. The Total LoP, which can be calculated using the same method as LoP at each response stage, conveys the total lockdown effect on urban air pollution while the Unit LoP characterizes the detailed recovery process.

3. Results and discussion

In this section, comparative research was carried out to characterize the trends of various air pollutants at different lockdown stages in the four cities and to identify their interruption-recovery pattern during COVID-19. Building on this, an RDD analysis of urban air quality was performed, to verify the significance of the variation in pollutant concentrations and explore the actual inflection point in the interruption-recovery patterns. Additionally, comparisons of general trends of various air pollutant concentrations between during the pandemic in 2020 and the same time in 2018 and 2019 were implemented, to better understand the interruption-recovery pattern. Patterns of loss of

![Fig. 5. Pollutant concentrations during the different lockdown stages in four Chinese cities under COVID-19.](image-url)
performance were also analyzed to evaluate the interruption-recovery patterns, with the same RDD analysis of the differences in pollutant concentrations conducted to further verify the patterning of the interruption-recovery trajectory of the difference in pollutant concentrations during the same period of 2020 vs. 2018–2019.

3.1. Variation in urban air quality before and during COVID-19

The basic urban air pollution interruption-recovery pattern of Fig. 2 (a) asserts that air pollutant concentrations (except for O₃) at the four different response stages would show the trend of first decreasing and then recovering to the original equilibrium. To test this hypothesis, for each pollutant, variation in its concentration was compared under different lockdown policies during the COVID-19 in 2020 (Fig. 5). Then, general trends in the variation of NO₂ and PM₁₀₂.₅ concentrations are shown in Fig. 6.

Different urban lockdown policies during COVID-19 evidently improved short-term air quality for all four megacities in China. As seen in Fig. 5(a) and (c), NO₂ and PM₁₀ emissions presented a similar pattern, in that their concentration levels were first significantly reduced and then gradually recovered, which matched up well with the lockdown policies during the pandemic. Considering that the NO₂ mainly results from traffic emissions [10], restrictions on people’s travel under the earlier urban lockdown policies effectively reduced on-road vehicular activities and thus decreased the NO₂ concentrations. Furthermore, the NO₂ and PM₁₀ concentrations at Level III showed a trend of decreasing again. Similarly, the emissions of PM₁₀₂.₅ and CO also significantly declined as shown in Fig. 5(b) and (f) respectively. Unlike the other pollutants, PM₁₀₂.₅ displayed a pattern of gradual decrease across different lockdown stages, lacking a concentration recovery process. One possible reason is that PM₁₀₂.₅ mostly originates from emissions by industrial activities, most of which remained disabled despite the reopening that occurred in all four cities. However, the overall level of CO continually declined, indicating that CO experienced a long-term persistent effect. From Fig. 5(d) we learned that SO₂ emissions exhibited a relatively stable trend during the pandemic, suggesting that the SO₂ source is mainly industrial emissions rather than transportation.

As illustrated by Fig. 5(e), the trends of O₃ concentrations under the COVID-19 lockdown differed considerably from that of other air pollutants. The O₃ concentration levels rose sharply after the implementation of the lockdown policies during the pandemic and rose continually through Level III. The main explanation for this lies with the pronounced reduction of industrial activities and vehicular emissions during the pandemic. This phenomenon led to a sharp drop in NOx concentrations that exceeded the decline in VOC concentrations [11], thereby lessening the titration effect of NOx towards ozone [53,54]. Overall, under COVID-19, the trend of the O₃ concentration was the opposite of that found for other pollutants.

As Fig. 6 shows, although being two typical pollutants, NO₂ and PM₁₀₂.₅ had different trends during the pandemic. However, a typical loss and recovery process was observed for both NO₂ and PM₁₀₂.₅, consisting of an evident decrease at the cutoff of Level I and a notable recovery around the cutoff of Level II and Reopen (i.e., reopening). However, these results are based on observation data and the actual inflection point was not yet confirmed (i.e., whether it occurred at the cutoff of Level II or Reopen).

In summary, the general trends of air pollutants except for O₃ all showed a gradual decrease, but this did not conform to the basic interruption-recovery pattern depicted in Fig. 2(a). The seasonal factors are one of the main reasons for this phenomenon, which would be discussed in detail in Section 3.2. Nevertheless, we are able to observe the process of loss and recovery, when going from Level I to Level II.

3.2. RDD analysis of the effect of COVID-19 lockdown policies on urban air pollutants and the characteristics of air pollution interruption-recovery patterns during COVID-19

To uncover the predominant interruption-recovery pattern of urban air pollution, the RDD model was applied to assist in evaluating the effects of different lockdown policies upon the variation in pollutant concentrations and to distinguish the inflection points in the interruption-recovery pattern when controlling for other confounding factors. In this section, Level I, Level II, and Level III represent the time period of three urban lockdown policies at different levels, while the cutoff selected in the RDD model is the start date of each Level. To ensure the reliability and effectiveness of our RDD estimates, a robustness test was also performed and the results are presented in the appendix.

Table 3 presents the trends for common urban air pollutants and the standard errors during the implementation of Level I. The start date of Level I was set as the RDD cutoff. There are several meaningful findings, summarized as follows:

![Fig. 6. Variation in the NO₂ and PM₁₀₂.₅ concentrations over time in 2020. The white triangles are the cutoffs of different lockdown stages and the red triangles indicate when the reopening occurred ('Reopen'). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)](image-url)
Effects of Level I on air pollutants across four metropolises in China (from October 1, 2019 to August 31, 2020).

| City       | AQI   | NO₂  | PM₂.₅ | PM₁₀ | CO    | SO₂  | O₃     |
|------------|-------|------|--------|------|-------|------|--------|
| Shanghai (G) | −0.545** (0.206) | −0.768*** (0.191) | −0.588* (0.243) | −0.295 (0.241) | −0.255** (0.087) | −0.037 (0.090) | 0.266** (0.091) |
| Tianjin    | −0.139 (0.279) | −0.746*** (0.124) | −0.092 (0.323) | −0.301 (0.284) | −0.371 (0.238) | 0.024 (0.141) | 0.614*** (0.152) |
| Guangzhou | −0.411** (0.158) | −0.982*** (0.103) | −0.320 (0.196) | −0.666** (0.190) | −0.271*** (0.055) | −0.087 (0.055) | 0.431*** (0.099) |
| Wuhan      | −0.315* (0.112) | −0.703*** (0.118) | −1.126*** (0.219) | −0.344* (0.121) | −0.392*** (0.068) | −0.071 (0.078) | 0.411*** (0.076) |
| Shanghai (T) | −0.894*** (0.065) | −0.666*** (0.233) | −0.828* (0.296) | −0.491*** (0.149) | −0.197 (0.140) | 0.956* (0.366) |

Notes: (1) ***, **, and * represent statistical significance at alpha levels of 0.001, 0.01, and 0.05, respectively. (2) G and T refer to general station and traffic station, respectively.

(1) At the time cutoff of Level I, the NO₂ concentrations decreased significantly while the O₃ concentrations increased significantly across the four cities, indicating that NOₓ and O₃ were greatly affected by anthropic activities. The SO₂ concentrations showed less significant differences during the pandemic because the SO₂ is less affected by traffic emissions. The PM₂.₅, PM₁₀, and CO concentrations also exhibited a significant trend of decline in most cities.

(2) In terms of Tianjin, its urban air quality was least affected by Level I compared with the other three cities. This could be explained by the fact that central heating and calm weather there in winter probably led to an accumulation of air pollutants, thus maintaining urban air pollution at a higher level [13]. By contrast, Shanghai, Wuhan, and Guangzhou presented similar patterns, in that their air pollutant concentrations declined significantly at the time cutoff of Level I.

(3) Compared with the air pollutants' data from general monitoring stations in Shanghai, the concentrations of air pollutants at traffic monitoring stations presented stronger declines, except for SO₂.

Table 3

Considering that the RDD model could eliminate confounding factors, the implementation of the lockdown policy at Level I could substantially affect the variation in pollutant concentrations across the four metropolises. Specifically, the lockdown policy at Level I significantly reduced the concentrations of all air pollutants except O₂. As presented in Table 4 and Table 5, the lockdown policies at Level II and Level III had little effect on air pollutant concentrations. These results indicate the Level II and Level III lockdown policies hardly brought any improvement to urban air quality, and the inflection point between their respective loss and recovery was not the time cutoff of Level II.

Table 4

3.3. Variation in air quality between the lockdown period in 2020 and the same period in 2018–2019

Because the interruption-recovery pattern can be strongly influenced by seasonal changes in pollutant concentrations, the air pollutant concentrations in the lockdown period in 2020 were compared with the average levels during the same period in 2018–2019, to further evaluate the interruption-recovery pattern. To clarify the interruption-recovery pattern, this comparison was also done based on air pollutants’ data between the peak and non-peak hours.

The three air pollutants (i.e., NO₂, PM₂.₅, and O₃) were selected for further study, due to the typical and differing characteristics in the variation of concentrations of these three air pollutants. Several meaning findings are summarized as follow and presented in Fig. 7 and Fig. 8:

(1) Except for O₃, air pollutant concentrations during the lockdown period in 2020 first decreased significantly at the time cutoff of Level I and then gradually recovered at the time cutoff of Reopen, while O₃ showed the opposite pattern. The differences in NO₂ concentrations between the lockdown period in 2020 and the same time in 2018–2019 were more pronounced than those for PM₂.₅ and O₃.

(2) The results suggested that the effects of different lockdown policies under COVID-19 in 2020 on urban air quality were greater during peak hours than non-peak hours. A plausible reason is that lockdown policies restricted people’s travel demands and the enterprises were not allowed to reopen until March 10, 2020. These results also suggest that anthropic activities can have large and negative impacts on urban air quality.

Our findings also indicate that even during the same period in 2018 and 2019 corresponding to the lockdown in 2020, the air pollutants’ concentration still presented a trend of gradually decreasing over time. However, the differences in pollutant concentrations between the
3.4. Patterns of loss of performance and the characteristics of interruption-recovery patterns of the year-on-year air pollution difference between the lockdown period in 2020 and the same period in 2018–2019

To gain more insights into the characteristics of the recovery process, the differences in air pollutant concentrations between the lockdown period in 2020 and the same period in 2018–2019 were further studied in detail. To quantify the effect of the COVID-19 lockdown policies, we utilized the concept of Loss of Performance (LoP) [52]. Specifically, as shown in Figs. 7 and 8, LoP and Unit LoP were respectively calculated according to Equation (2) and Equation (3). The results for Unit LoP and Total LoP of six regulatory air pollutants during peak and non-peak periods across the four megacities are presented in Table 7.

In Table 7, the Unit LoP of air pollutants except for O₃ showed a decreasing trend with the changed lockdown policies against the COVID-19. The difference between the general trend in the variation of a given pollutant’s concentration during COVID-19 and its original equilibrium was gradually reduced. This result also reveals the interruption-recovery pattern of the difference in pollutant concentrations during the same period of 2020 vs. 2018–2019, resembling Fig. 2(c), in that the difference of pollutant concentrations first showed a significant decline at the cutoff of Level I but then gradually recovered to a new equilibrium. Additionally, for NO₂ and O₃, the differences in their Unit LoP...
between peak hours and non-peak hours were notably larger than those of other pollutants. These results indicate that \( \text{NO}_2 \) and \( \text{O}_3 \) concentration levels are greatly affected by traffic activities \([5, 11]\). Furthermore, the effects of different COVID-19 lockdown policies on urban air quality during peak hours were more pronounced than those during the non-peak hours.

To better understand the dynamics of pollutant concentrations during the lockdown period in 2020 vis-à-vis the same period in 2018–2019, the corresponding percentage changes of pollutant concentrations were also calculated and compared. The results are presented in Fig. 9 and Table 8.

In Fig. 9, the curve of percentage changes in the pollutant concentrations showed a similar trend to the basic interruption-recovery pattern corresponding to Fig. 2(a). The percentage change in the various pollutants across four cities generally suggested a decrease during the loss process followed by an increase during the recovery process. These results further demonstrate that the interruption-recovery pattern of urban air pollution under the COVID-19 in 2020 presented some differences compared with the interruption-recovery pattern of the year-on-year air pollution difference. Specifically, the concentrations of \( \text{NO}_2 \) most resembled the basic interruption-recovery pattern, which indicated this air pollutant was the one most affected by the lockdown policies. Yet we could not confirm the above conclusions based only on comparative research given the likely influence from confounding factors. Hence, an RDD analysis was relied upon to assess the effects of different lockdown policies on the difference in pollutant concentrations during the same period between 2020 and 2018–2019.

The cutoffs were set using the same method as above in Section 3.2, i.e., the start dates of Level I, Level II, and Level III. Here, we selected the \( \text{NO}_2 \) as a typical example, quantifying the variation in its concentrations in Shanghai during the pandemic in 2020 and the same period in 2018–2019.

In Fig. 10, the percentage differences in \( \text{NO}_2 \) concentrations in Shanghai between the pandemic in 2020 and the same period in 2018–2019 constantly declined as the lockdown policies against COVID-19 changed. Concerning that the RDD estimates were not significant, the loss and recovery of \( \text{NO}_2 \) concentrations was in fact a gradual process, where no inflection point was found in its interruption-recovery pattern.
This result indicates that the interruption-recovery pattern showed no sudden change, corresponding to Fig. 2(c), except for the time cutoff of Level I. The main difference in the interruption-recovery pattern as revealed in Fig. 2(b) and (c) is that the latter’s pattern entails a gradual process of recovery. Additionally, that no inflection point was found between the recovery process and the new equilibrium indicates the NO\textsubscript{2} concentrations at either Level II or Level III exhibited less significant variation. Therefore, the interruption-recovery pattern of the year-on-year air pollution difference presented a similar pattern as the basic loss-recovery process but it also harbored a gradual process of recovery.

4. Conclusions

In this study, the air pollutant data collected from national environmental monitoring stations across four metropolises in China (Shanghai, Wuhan, Guangzhou, and Tianjin) were used to address two research objectives: to evaluate the interruption-recovery patterns of urban air pollution under COVID-19, and to further analyze the impacts of different lockdown policies on urban air quality at different response stages. To eliminate the confounding terms, the regression discontinuity design (RDD) model was utilized to explore the effects of different lockdown policies on urban air quality and investigate the specific recovery patterns of urban air pollution under the interruption of COVID-19 lockdown policies. Several meaningful findings are summarized as follows:

1. The general trends for pollutant concentrations across the four cities were similar. To be specific, the NO\textsubscript{2} concentrations showed the most significant variation as the different lockdown policies shifted among response stages. The O\textsubscript{3} concentrations presented...
Fig. 10. Regression discontinuity plot of the percentage differences in NO$_2$ concentrations in Shanghai during the pandemic in 2020 vs. the same period in 2018–2019.

an opposite pattern compared with the other air pollutants. Both NO$_2$ and O$_3$ were strongly affected by traffic emissions. However, the SO$_2$ concentrations were maintained at a relatively stable level during the pandemic, indicating that pollutant levels are determined less by traffic emissions and more by industrial sources.

(2) For most of the air pollutants (except for O$_3$), their concentrations exhibited a significant trend of decreasing during the COVID-19 period in 2020, compared with those during the same period in 2019. Moreover, the typical process of loss and recovery was found between Level I and the time around reopening (the Reopen stage).

(3) The variation in the urban air quality at the onset of COVID-19 was mainly affected by the lockdown policy. But after Level III, seasonal factors became the main factor driving changes in the air pollutant concentrations. Hence, the interruption-recovery pattern of urban air pollution under COVID-19 in 2020 was detected, whereby air pollutant concentrations first decreased significantly at the cutoff of Level I, then gradually recovered at reopening (Reopen), decreasing again after Level III.

(4) The effects of COVID-19 on urban air quality underwent a long and gradual recovery process. Hence, the interruption-recovery pattern of the difference in pollutant concentrations during the same period of 2020 vs. 2018–2019 was revealed in this study, corresponding to the loss, adaptation, and recovery of urban air quality from 2018 to 2019 to 2020. The interruption-recovery curve indicates that pollutant concentration difference between 2020 and 2018–2019 initially decreased significantly at the cut-off of Level I and then recovered to a new equilibrium state. For example, in Shanghai, the NO$_2$ concentration decreased by 11.47%, 33.68%, 17.99%, –6.84% during Pre-lockdown, Level I, Level II, Level III respectively, which further confirms the interruption-recovery curve of air pollution difference.

(5) The two different air pollution interruption-recovery patterns highlighted a process of loss and recovery between Level I and Reopen. However, the major difference between the two interruption-recovery patterns was that the recovery pattern of urban air pollution under the interruption of COVID-19 in 2020 decreased again after the recovery process, showing clear cutoffs (i.e., Level I and the start date of Reopen). Further, the recovery process of air pollution difference between the lockdown period in 2020 and the same time in 2018–2019 presented a gradual trend, with no clear inflection points found in the interruption-recovery curve.

The main novelty and contributions of this research are as follows:

(1) We found and explored the interruption-recovery patterns of urban air pollution during the COVID-19 lockdown period (Fig. 2(b)), and the interruption-recovery patterns of air pollution difference between 2020 and 2018–2019 (Fig. 2(c)). The pattern can assist policymakers in better understanding the dynamics of urban air pollution and optimizing the decision-making of lockdown policies.

(2) This study quantified the effects of different lockdown policies against COVID-19 upon urban air quality. The results can assist policymakers in anticipating the potential outcomes of differing lockdown policies.

(3) The RDD model was developed and fitted to the empirical data in this paper. These results demonstrated that the RDD method was more effective and accurate in analyzing the effects of time-based policy under the impact of confounding short-term factors (i.e., meteorological factors).

(4) The concentrations of pollutants significantly decreased but were not fully eliminated, even under the most severe lockdown policies. Therefore, in addition to a tailored lockdown policy, some parallel strategies—e.g., the adjustment of industry structures and the adoption of clean energy—should also be employed to further improve urban air quality.

One limitation of this paper is that our findings focused on metro-polises in China, while other global cities may present different interruption-recovery patterns of urban air pollution. Future studies could consider other cities or regions worldwide, to further explore the interruption-recovery patterns of urban air pollution and elucidate inherent mechanisms of the variation in urban air quality during the COVID-19 pandemic.

CRediT authorship contribution statement

The authors confirm their respective contribution to the paper as follows: study conception and design: Wan-Jin Cai; data collection: Wan-Jin Cai, Cui-Lin Wu; analysis and interpretation of results: Wan-Jin Cai; draft manuscript preparation: Wan-Jin Cai; Hong-Wei Wang, Kai-Fa Lu, Zhong-Ren Peng, and Hong-Di He co-wrote the paper. All the authors reviewed the results and approved the final version of the manuscript.
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.

Acknowledgement

This research is supported by the National Planning Office of Philosophy and Social Science (No. 16ZDA048), the National Natural Science Foundation of China (No. 12072195), and the Science and Technology Project of Guangzhou (No. 201803030032).

Appendix

Robustness Test

A regression discontinuity analysis should include the robustness tests of the model results [51]. Only with such a robustness test are the conclusions derived from the RDD model meaningful. This paper used the covariate (i.e., meteorological factors) as the outcome variable to perform the RDD analysis and determine whether the covariate has an actual cutoff (a ‘jump’) at the original cutoff. If there found to be a jump at the cutoff, the results of the RDD analysis are interfered and hence are meaningless. The meteorological factors (temperature, wind speed, and wind direction) were used as pseudo-result variables to perform the RDD analysis. The order selection was determined using the same method as above, this being set to 2. This resulted in a coefficient of cutoff d that equaled 0.04, which is very small. The p-value was much higher than 0.05, thus showing little statistical significance. Hence, this result indicates the meteorological covariate was continuous at the cutoff and would not have interfered with the outcome variable of interest.

This paper used a non-parametric statistical test method proposed by Ref. [55]. This method tests whether the reference variable distribution at the cutoff is continuous and whether a jump exists in the reference variable distribution at that cutoff. The resulting p-value was much higher than 0.05, thus showing little statistical significance. Hence, this result indicates the meteorological covariate was continuous at the cutoff and would not have interfered with the outcome variable of interest.

Some pseudo-cutoffs may also exist when performing an RDD analysis. These pseudo-cutoffs usually show a significant jump in the outcome variables with the continuous variable X changing and could lead to an incorrect result. Therefore, this paper also conducted a pseudo-cutoff test to exclude such circumstances. When performing the RDD from pre-lockdown to Level I, and likewise from Level I to Level II, 50% of the positions before and after the cutoff for the pseudo-cutoff test were both selected. Specifically, the pollutants’ data from December 1, 2019 (–50%) to 15 February 15, 2020 (–50%) and from February 15, 2020 (–50%) to 5 April 5, 2020 (–50%) were separately selected for a pseudo-cutoff analysis. Their resulting p-values exceeded 0.05, with no obvious jumps in the outcome variables. To illustrate this, the megacity Wuhan is selected in this experiment and the NO2 concentrations here exhibit the most significant change in the pseudo-cutoff test. As Fig. A1 shows, no significant jumps in the outcome variables were observed at all three pseudo-cutoffs. Therefore, the robustness of the RDD model has been ensured.

References

[1] Z. Fu, D.J. Li, O. Hararuk, C. Schwalm, Y.Q. Luo, L.M. Yan, S.L. Niu, Recovery time and state change of terrestrial carbon cycle after disturbance, Environ. Res. Lett. 12 (10) (2017) 10, https://doi.org/10.1088/1748-9326/aa885c.
[2] T.H. Nguyen, S.D. Jones, M. Soto-Berelov, A. Haywood, S. Hislop, A spatial and temporal analysis of forest dynamics using Landsat time-series, Rem. Sens. Environ. 217 (2018) 461–475, https://doi.org/10.1016/j.rse.2018.08.028.
[3] D. Henry, J.E. Ramirez-Marquez, Generic metrics and quantitative approaches for system resilience as a function of time, Reliab. Eng. Syst. Saf. 99 (2012) 114–122, https://doi.org/10.1016/j.ress.2011.09.002.
[4] S.Y. Wang, Y.L. Zhang, J.L. Ma, S.Q. Zhu, J.Y. Shen, P. Wang, H.L. Zhang, Responses of decline in air pollution and recovery associated with COVID-19 lockdown in the Pearl River Delta, Sci. Total Environ. 756 (2021) 9, https://doi.org/10.1016/j.scitotenv.2020.143868.
[5] H.W. Wang, X.B. Li, D.S. Wang, J.H. Zhao, H.D. He, Z.R. Feng, Regional prediction of ground-level ozone using a hybrid sequence-to-sequence deep learning approach, J. Clean. Prod. 253 (2020) 12, https://doi.org/10.1016/j.jclepro.2019.119841.
[6] J.F. Wang, X.Y. Xu, S.M. Wang, S.T. He, P. He, Heterogeneous effects of COVID-19 lockdown measures on air quality in Northern China, Appl. Energy 282 (2021) 10, https://doi.org/10.1016/j.apenergy.2020.116179.
[7] P. Lal, A. Kumar, S. Kumar, S. Kumari, P. Sakkia, A. Dayanandan, D. Adhikari, M. L. Khan, The dark cloud with a silver lining: assessing the impact of the SARS COVID-19 pandemic on the global environment, Sci. Total Environ. 732 (2020), 139297, https://doi.org/10.1016/j.scitotenv.2020.139297.
[8] H. Xu, C.H. Yan, Q.Y. Fu, K. Xiao, Y.M. Yu, D.M. Han, J.P. Cheng, Possible environmental effects on the spread of COVID-19 in China, Sci. Total Environ. 731 (2020) 7, https://doi.org/10.1016/j.scitotenv.2019.139211.
[9] R. Bao, A.C. Zhang, Does lockdown reduce air pollution? Evidence from 44 cities in northern China, Sci. Total Environ. 731 (2020) 12, https://doi.org/10.1016/j.scitotenv.2020.139052.
[10] Q. Wang, M. Su, A preliminary assessment of the impact of COVID-19 on environment? A case study of China, Sci. Total Environ. 728 (2020) 10, https://doi.org/10.1016/j.scitotenv.2019.138915.
[11] L. Li, Q. Li, L. Huang, Q. Wang, A.S. Zhu, J. Xu, A. Chan, 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, Sci. Total Environ. 732 (2020) 11, https://doi.org/10.1016/j.scitotenv.2019.139282.
[12] P. Sicard, A. De Marco, E. Agathokleous, Z. Feng, X. Xu, E. Paolletti, V. Calatayud, Amplified ozone pollution in cities during the COVID-19 lockdown, Sci. Total Environ. 735 (2020), 139542, https://doi.org/10.1016/j.scitotenv.2019.139542.
[13] Q. Liu, J.T. Harris, L.S. Chiu, D. Sun, P.R. House, M. Yu, C. Yang, Spatiotemporal impacts of COVID-19 on air pollution in California, USA, Sci. Total Environ. 750 (2021), 141592, https://doi.org/10.1016/j.scitotenv.2020.141592.
[14] K. Shehzad, F. Bilgili, E. Kocak, L. Xiaoxing, M. Ahmad, COVID-19 outbreak, lockdown, and air quality: fresh insights from New York City, Environ. Sci. Pollut. Res. Int. (2021), https://doi.org/10.1007/s11356-021-13556-8.
[15] A.R. Toro, F. Catalan, F.R. Urdanivia, J.F. Rojas, C.A. Manzano, R. Seguel, M. A. Leiva-Guzman, Air pollution and COVID-19 lockdown in a large South American city: Santiago metropolitan area, Chile, Urban Clim 36 (2021), 100803, https://doi.org/10.1016/j.uclim.2021.100803.
A. Viana-Soto, I. Aguado, J. Salas, M. Garcia, Identifying post-fire recovery trajectories and driving factors using land sat time series in fire-prone mediterranean pine forests, Rem. Sens. 12 (9) (2020) 25, https://doi.org/10.3390/rs12091999.

Z. Yang, J. Li, C.E. Zipper, Y.Y. Shen, H. Miao, P.F. Donovan, Identification of the disturbance and trajectory types in mining areas using multimodal remote sensing images, Sci. Total Environ. 644 (2018) 916–927, https://doi.org/10.1016/j.scitotenv.2018.06.341.

Q. Han, Y. Liu, Z.L. Lu, Temporary driving restrictions, air pollution, and contemporaneous health: evidence from China, Reg. Sci. Urban Econ. 84 (2020) 15, https://doi.org/10.1016/j.regsciurbeco.2020.103572.

F.C. Huang Bin, D. Wang, Causal inference in education research: principles and applications of related methods, J. East China Normal Univ. Educ. Sci. 35 (4) (2017) 1–14+134, https://doi.org/10.16382/j.ekcn.2017.04.001.

D.S. Lee, T. Lemieux, Regression discontinuity designs in economics, J. Econ. Lit. 48 (2) (2010) 281–355, https://doi.org/10.1257/jel.48.2.281.

M.J. Lee, Y. Savada, Review on difference in differences, Korean Economic Review 36 (1) (2020) 135–173. Retrieved from <Go to IS>://WOS:000505642100005

M. Bertanha, Regression discontinuity design with many thresholds, J. Econom. 218 (1) (2020) 216–241, https://doi.org/10.1016/j.jeconom.2019.09.010.

C. Hausman, D.S. Rapson, Regression discontinuity in time: considerations for empirical applications, in: G.C. Rauser, G. C, D. Zilberman (Eds.), Annual Review of Resource Economics, vol. 10, Annual Reviews, Palo Alto, 2018, pp. 533–552.

J.Y. Choi, M.J. Lee, Regression discontinuity: review with extensions, Stat. Pap. 58 (4) (2017) 1217–1246, https://doi.org/10.1007/s00362-016-0745-x.

J.H. Seinfeld, S.N. Pandis, Atmospheric Chemistry and Physics: from Air Pollution to Climate Change, John Wiley & Sons, New York, 2016.

H.D. He, H.O. Gao, Particulate matter exposure at a densely populated urban traffic intersection and crosswalk, Environ. Pollut. 268 (2021), 115931.

K.F. Lu, H.D. He, H.W. Wang, X.B. Li, Z.R. Peng, Characterizing temporal and vertical distribution patterns of traffic-emitted pollutants near an elevated expressway in urban residential areas, Build. Environ. 172 (2020) 11, https://doi.org/10.1016/j.buildenv.2020.106678.

D.L. Thistlethwaite, D.T. Campbell, Regression-discontinuity analysis-an alternative to the ex-post-facto experiment, J. Educ. Psychol. 51 (6) (1960) 309–317, https://doi.org/10.1037/h004519.

M. Huskova, M. Maciak, Discontinuities in robust nonparametric regression with alpha-mixing dependence, J. Nonparametric Statistics 29 (2) (2017) 447–475, https://doi.org/10.1080/10485252.2017.1303661.

D. Anderson, K. Burnham, Model Selection and Multi-Model Inference, Springer-Verlag, New York, 2004.

H. Akaile, A new look at the statistical model identification, IEEE Trans. Automat. Contr. 19 (6) (1974) 716–723.

A. Gelman, G. Imbens, Why high-order polynomials should not be used in regression discontinuity designs, J. Bus. Econ. Stat. 37 (3) (2019) 447–456, https://doi.org/10.1080/07350015.2017.1366909.

D. Anderson, K. Burnham, Model Selection and Multi-Model Inference, Springer-Verlag, New York, 2004.

H.S. Bloom, Modern regression discontinuity analysis, Journal of Research on Educational Effectiveness 5 (1) (2012) 43–82, https://doi.org/10.1080/19345747.2011.578707.

A. Jentsch, H.C. Kapper, J.R. Ziemke, The status of air quality in the United States during the COVID-19 pandemic: a remote sensing perspective, Rem. Sens. 13 (3) (2021), https://doi.org/10.3390/rs13030365.

M.J. Lee, Y. Sawada, Review on difference in differences, J. Econom. 218 (1) (2020) 216–241, https://doi.org/10.1016/j.jeconom.2019.09.010.

C. Hausman, D.S. Rapson, Regression discontinuity in time: considerations for empirical applications, in: G.C. Rauser, G. C, D. Zilberman (Eds.), Annual Review of Resource Economics, vol. 10, Annual Reviews, Palo Alto, 2018, pp. 533–552.

J.Y. Choi, M.J. Lee, Regression discontinuity: review with extensions, Stat. Pap. 58 (4) (2017) 1217–1246, https://doi.org/10.1007/s00362-016-0745-x.

J.H. Seinfeld, S.N. Pandis, Atmospheric Chemistry and Physics: from Air Pollution to Climate Change, John Wiley & Sons, New York, 2016.

H.D. He, H.O. Gao, Particulate matter exposure at a densely populated urban traffic intersection and crosswalk, Environ. Pollut. 268 (2021), 115931.

K.F. Lu, H.D. He, H.W. Wang, X.B. Li, Z.R. Peng, Characterizing temporal and vertical distribution patterns of traffic-emitted pollutants near an elevated expressway in urban residential areas, Build. Environ. 172 (2020) 11, https://doi.org/10.1016/j.buildenv.2020.106678.

D.L. Thistlethwaite, D.T. Campbell, Regression-discontinuity analysis-an alternative to the ex-post-facto experiment, J. Educ. Psychol. 51 (6) (1960) 309–317, https://doi.org/10.1037/h004519.

M. Huskova, M. Maciak, Discontinuities in robust nonparametric regression with alpha-mixing dependence, J. Nonparametric Statistics 29 (2) (2017) 447–475, https://doi.org/10.1080/10485252.2017.1303661.

D. Anderson, K. Burnham, Model Selection and Multi-Model Inference, Springer-Verlag, New York, 2004.

H. Akaile, A new look at the statistical model identification, IEEE Trans. Automat. Contr. 19 (6) (1974) 716–723.

A. Gelman, G. Imbens, Why high-order polynomials should not be used in regression discontinuity designs, J. Bus. Econ. Stat. 37 (3) (2019) 447–456, https://doi.org/10.1080/07350015.2017.1366909.

D. Anderson, K. Burnham, Model Selection and Multi-Model Inference, Springer-Verlag, New York, 2004.

H.S. Bloom, Modern regression discontinuity analysis, Journal of Research on Educational Effectiveness 5 (1) (2012) 43–82, https://doi.org/10.1080/19345747.2011.578707.