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Air pollution rebound and different recovery modes during the period of easing COVID-19 restrictions

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HIGHLIGHTS

- This paper investigated the impact of recovery on air pollution rebound.
- We focused on the period of easing COVID-19 restrictions for 119 cities in China.
- “Recovery” was constructed by a city-pair inflow index with an innovative method.
- There was a 3 %-6 % rebound in three air pollutants when recovery increased by 10 %.
- Five recovery modes were got by counterfactual framework and time series clustering.

ARTICLE INFO

Editor: Anastasia Paschalidou

Keywords:
The period of easing COVID-19 restrictions Air pollution rebound Recovery modes Counterfactual analysis Time series clustering Wavelet transform

ABSTRACT

Although COVID-19 lockdown policies have improved air quality in numerous countries, there is a lack of empirical evidence on the extent to which recovery has resulted in air pollution rebound, and the differences and similarities among regions' recovery modes during the period of easing COVID-19 restrictions. Here, we used daily air quality data and the recovery index constructed by a city-pair inflow index for 119 cities in China to quantify the impact of recovery on air pollution from March 2 to October 30, 2020. Findings show that recovery has significantly increased air pollution. When the recovery level increased by 10 %, the concentration of PM2.5, SO2, and NO2 respectively deteriorated by 1.10, 0.33, 1.25 μg/m³, and the average growth rates of three air pollutants were about 3 %-6 %. Moreover, we used the counterfactual framework and time series clustering with wavelet transform to cluster the rebound trajectory of air pollution for 17 provinces into five recovery modes. Results show that COVID-19 has further intensified regional differentiations in economic development ability and green recovery trend. Three northwestern provinces dependent on their resource endowments belong to energy-intensive recovery mode, which have experienced a sharp rebound of air pollution for two months, thereby making green recovery more challenging to achieve. Three regions with a diversified industrial structure are in industrial-restructuring recovery mode, which has effectively returned to a normal level through adjusting industrial structure and technological innovation. Owing to local policies and the outbreak of COVID-19 in other countries, six provinces in policy-oriented and international trade-oriented recovery modes have not fully recovered to the level without COVID-19 until October 2020. The result highlights the importance of diversifying industrial structure, technological innovation, policy flexibility and industrial upgrading for different recovery modes to achieve long-term green recovery in the future.

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1. Introduction

COVID-19 has resulted in an unprecedented global crisis on people's lives and economic development (Han et al., 2020). As lockdown policies (e.g., travel restrictions, closure of factories) adopted by numerous countries have reduced infectious cases of COVID-19, they have also significantly improved countries' air quality. The literature has shown that lockdown measures improved air quality in China by approximately 7.8%–17% (He et al., 2020; Bao and Zhang, 2020; Liu et al., 2020a; Wang et al., 2021a; Wang et al., 2021c; Zhang et al., 2021b), by 17%–18% across 71 provinces in Italy (Malpede and Percoco, 2021), and by 3% in 48 core-based statistical areas of the US (Ghosal and Saha, 2021). However, the improvement of air quality and COVID-19 prevention and control were achieved by sacrificing human mobility, which has a heavy cost on socio-economic development.

As the first wave of COVID-19 has been effectively controlled, the recovery process starting from abolishing lockdown policies and traffic controls could be reflected from human mobility, which may also influence air pollution. Therefore, how to recover from COVID-19 and how far to achieve a green and sustainable recovery are urgent and necessary issues for the majority of countries during the period of easing COVID-19 restrictions. On the one hand, quantifying the impact of COVID-19 recovery on air pollution is one of important aspects of national or regional air quality management. Given that the improvement of air quality at the expense of the economy cannot produce long-term environmental benefits (Guerrero et al., 2020), the relationship between recovery and air pollution could reflect the extent of atmospheric environment destruction through recovering from exogenous shocks. On the other hand, owing to the close relationship between air pollution levels and recovered economic activities (Mele et al., 2021), regions' air quality rebound trajectories could reflect different economic recovery modes. Hence, this paper could make governments and policy makers in regions with different industrial structures and resource endowments realize their challenges and required inputs to achieve long-term green recovery in the future.

As the first economy to ease COVID-19 restrictions and start economic recovery in 2020, China could have implications for other economies or regions with similar stages of industrialization, air quality management or COVID-19 prevention and control. China is a large country and has cities or provinces with different types of industrial structure and resource endowments (Shan et al., 2018), and the recovery modes of which could be representative. Given China's exposure to COVID-19 outbreaks in other countries and reoccurrence in localized regions, this country is experienced in balancing COVID-19 prevention and economic recovery during the period of easing COVID-19 restrictions.

However, previous literature's definitions of recovery and the period of easing COVID-19 restrictions have been varied. Instead of relating the index to human mobility, recent studies have either divided it into different stages (Wang et al., 2021b; Bhatti et al., 2022; Zhang et al., 2020a; Bao et al., 2020a) or used indirect measures (e.g., the proportion of enterprises with electricity consumption exceeding 30%, a rebound index constructed by air pollution levels) to describe this continuous variable (Zheng, 2022; Feng et al., 2022), which are relatively biased. Hence, “recovery” in the current paper is a ratio constructed by indices for human mobility, which measures the extent to which a city has returned to normal through work resumption and restarting economic production activities. The period of easing COVID-19 restrictions starts from the end of February 2020, when the first wave of COVID-19 in China has been relatively controlled and regional travel restrictions have gradually been lifted. Although COVID-19 has recurred from time to time during the period of easing COVID-19 restrictions, it is regarded as the “new normal”, which is manifested as recovering to a normal life under the potential risk and dynamic control of the pandemic.

Moreover, when discussing air pollution rebound during the period of easing COVID-19 restrictions, the majority of the studies have disregarded the importance of quantifying how and to what extent the recovery has resulted in air pollution rebound from the human mobility perspective. In particular, they have mainly used satellite-based observations (Ding et al., 2020; Zhang et al., 2020a; Zheng et al., 2020) or self-constructed global near-real-time activity data (Liu et al., 2020b) to show the rebound ratio of air pollution in different stages and indicate when it returns to the air pollution level before COVID-19. However, only a few empirical studies have quantified the causality between recovery and ambient air pollution during the period of easing COVID-19 restrictions. Zheng (2022) showed that a positive relationship cannot be seen between post-COVID-19 work resumption and regional air pollution for five provinces in Southern China during the early-stage recovery.

Lastly, for the heterogeneity of air pollution rebound, previous literature has not compared regions' similarities and differences and summarized into various recovery modes. These studies have only given simple descriptions for the rebound ratio of air pollution in different Chinese cities or provinces after comparing with the level during the lockdown period (Tao et al., 2021; Zhang et al., 2020a; Wang and Yang, 2021). Given that air pollution level is closely related to economic activities (Mele et al., 2021), the rebound trajectories of air pollution could directly reflect the economic recovery modes for regions with different industrial structures and resource endowments. However, no summary of various recovery modes has been made, thereby having minimal implications from a global perspective.

Therefore, the research questions of this paper are as follows: (1) To what extent has recovery resulted in air pollution rebound during the period of easing COVID-19 restrictions? (2) What are the differences and similarities for regions' recovery modes during the period of easing COVID-19 restrictions? First, we use the city-pair inflow index obtained from a website for big data traffic as a basis in constructing a recovery index as a proxy variable for the recovery process. Second, this paper employs a fixed-effect model to quantify the impact of recovery on air pollution by using a panel dataset for 119 cities in 17 provinces of China from March 2 to October 30, 2020. Third, we obtain the rebound trajectory of air pollution for each city by the counterfactual framework, which quantifies the degree of improvement or deterioration in air quality compared with the counterfactual situation without COVID-19. Lastly, we apply the wavelet transform and time series clustering for the daily rebound trajectory of air pollution in 17 provinces and cluster them into five groups. These five clusters are summarized as five recovery modes (i.e., energy-intensive, industrial-restructuring, policy-oriented, international trade-oriented, and less-impacting recovery modes).

This study contributes to the literature in several ways. First, by using the city-pair inflow index, we construct a recovery index from the perspective of human mobility to directly reflect the continuous recovery process. As a daily index related to human migration, the city-pair inflow index is sensitive to the extent of abolishing lockdown policies and traffic control. Thus, this constructed recovery index could reduce the bias of variable measurement and also be used as an explanatory variable to quantify the impact on air pollution rebound. Second, we construct a counterfactual framework based on daily meteorological conditions and atmospheric control policies in the sample period discussed in 2020. Unlike traditional DID models using the pre-COVID-19 level in 2020 or the same period in 2019 as a control group, this paper could better avoid bias resulting from seasonal heterogeneity and yearly changing air pollution control policies by having same daily factors between counterfactual and actual situations. Lastly, five recovery modes are identified through wavelet transform and time series clustering to reflect the recovery processes for regions with different industrial structures and resource endowments. The five recovery modes are not predetermined but are ex-post and defined based on the clustering results, thereby becoming more convincing in showing the similarity within modes and differences between modes.

The remainder of this paper is organized as follows. Section 2 introduces the data, model, and variables in detail. Section 3 presents the results and robustness checks. Section 4 discusses the results. Lastly, Section 5 concludes the paper and outlines the implications.
2. Research design

2.1. Sample selection and variables

To study the impact of recovery on air pollution and identify various recovery modes based on rebound trajectories, this paper compiles a day-by-city level dataset from March 2 to October 30, 2020, containing 119 cities at or above the prefecture-level in China's 17 provinces. The sample includes key cities for air pollution prevention and control, cities of significant economic importance, and regions with strong lockdown policies. Hence, the sample of this paper could be markedly representative when we study the relationship between economic recovery and air pollution rebound.

This paper uses the concentrations of PM$_{2.5}$, SO$_2$, and NO$_2$ to measure air pollution in cities. These data were obtained from China National Environmental Monitoring Center (CNEMC, http://www.cnemc.cn/). A lower concentration of air pollutants implies better air quality. Moreover, this paper also studies the impact of recovery on a comprehensive measure of air pollution (i.e., daily air quality index, AQI) as a supplement.

The recovery index, as a key explanatory variable in this paper, is a ratio constructed by a city-pair inflow index (for details, see Section 2.2.1), which measures the extent to which a city has returned to normal through work resumption and restarting economic production activities during the period of easing COVID-19 restrictions. The city-pair inflow index is a daily inflow index between two cities from AutoNavi (Gaode, in Chinese, https://tp.map.autonavi.com/index.do), which is one of the largest companies for desktop and mobile mapping applications. This constructed recovery index based on human mobility could directly reflect the relaxation of traffic restrictions and economic vitality during the period of easing COVID-19 restrictions, which neither needs to break “recovery” into different stages (Wang et al., 2021b; Bhatti et al., 2022) nor has to use indirect measures to describe this continuous variable (Zheng, 2022; Feng et al., 2022).

Apart from the anthropogenic emission caused by recovery, meteorological conditions and heating are also important factors influencing daily air pollution. On the one hand, weather variables include temperature, pressure, and rain, which are based on 810 weather stations in 119 cities. These variables were collected from the shared dataset between China Meteorological Administration and CNEMC. This study follows Ramcharan (2010) and averages weather station data to obtain daily city-level observations. On the other hand, Qinling-Huaihe Line indicated that cities situated north of the demarcation line are provided with collective heating, but not for southern cities. Owing to geographical heterogeneity and different weather conditions annually, the start and end dates of winter heating are not identical (Cai et al., 2020). We collected these dates based on reports of urban thermal companies and official media in 2020.

The final dataset includes 17,822 observations after removing observations on weekends and statutory holidays, winsorizing outliers, and excluding missing values of some variables. We report the variable definitions of this dataset in Table A.1.

2.2. Methods

2.2.1. Measurement of the recovery index

To quantify the recovery process during the period of easing COVID-19 restrictions, this paper constructs the recovery index based on the city-pair inflow index:

\[
\text{Recovery}_{ij} = \frac{\Delta T_{i,j,2020}}{\Delta T_{i,j,2019}} = \frac{T_{i,j,2020} - T_{i,j,2019}}{T_{i,j,2019}} = \frac{\sum_{n=1}^{N_i} T_{i,j,n,2020} - T_{i,j,n,2019}}{\sum_{n=1}^{N_i} T_{i,j,n,2019}}
\]  

(1)

According to Eq. (1), the recovery index is constructed by three steps below. First, we use the city-pair index provided by AutoNavi to calculate the inter-city inflow index:

\[
T_{i,j,2020} = \sum_{\tau=1}^{\tau} T_{i,j,\tau,2020}
\]  

(2)

where $T_{i,j,\tau,2020}$ is the city-pair index reflecting the inflow from city $j$ to city $i$ on date $\tau$ in 2020 and $T_{i,j,\tau,2019}$ is the inter-city inflow index, which is the sum of city-pair inflow indices from the rest of the cities to city $i$ on date $\tau$ in 2020.

Second, given the effect of COVID-19 and migration during the Spring Festival, the intensity of population migration before and after the lockdown policies in 2020 are relatively different. Therefore, this paper follows Shi et al. (2021) and Zhang et al. (2020b) to reflect the relative changes in population migration and adopts the index before lockdown as a baseline to normalize the inter-city inflow index. The relative inter-city inflow in 2020 is as follows:

\[
\Delta \%_{i,j,2020} = \frac{T_{i,j,2020} - T_{i,j,2019}}{T_{i,j,2019}}
\]  

(3)

where $\Delta \%_{i,j,2020}$ is the relative inter-city inflow in city $i$ on date $\tau$ in 2020 and $T_{i,j,2019}$ is the baseline index, which is calculated by averaging the inter-city inflow index of city $i$ on weekdays of the second and third weeks before the Spring Festival of 2020. Given that the peak period of Spring Festival travel rush often happens in the last seven days before the first day of Chinese New Year, this relative inter-city inflow avoids the coincidence of flows between people returning home and working migration. Variables $T_{i, 2019}$, $Ti, 2020$ and $\Delta \%_{i,j,2020}$ can be obtained by using similar ways.

Lastly, the recovery index $Recovery_{ij}$ is quantified by the ratio between the relative inter-city inflow in city $i$ on date $\tau$ in 2020 and 2019 (Zhang et al., 2020b). The same date $\tau$ in 2020 and 2019 is defined as two days in the same week number and the same day of the week. For example, March 2, 2020 and March 4, 2019 are regarded as the same date because they fell on a Monday on the 10th week in 2020 and 2019. In constructing the recovery index, we assume that human mobility in the past few years without COVID-19 followed a similar migration pattern. The relative inter-city inflow in 2019 is used as a benchmark. The relative inter-city inflow of each city in 2020 is different from the situation before 2020 owing to COVID-19. Therefore, the recovery index quantifies the relative migration level in city $i$ on date $\tau$ in 2020 compared with the same date in 2019, thereby further reflecting the degree of recovery. When $Recovery_{ij}$ equals 100 %, the relative migration level in city $i$ on date $\tau$ in 2020 has returned to the level of the same date in 2019. When $Recovery_{ij}$ is less (more) than 100 %, the relative migration level in city $i$ on date $\tau$ in 2020 is lower (higher) than the same date in 2019.

2.2.2. Econometric models

To quantify the impact of recovery on air pollution during the period of easing COVID-19 restrictions, we apply the fixed-effect model in Eqs. (4) and (5) based on Bao and Zhang (2020) and Zheng (2022). Given that our dataset is a long panel with $N = 119$ and $T = 151$, it could be biased to apply the normal fixed-effect model “xtreg”, which is often suitable for a short panel with large N and small T. This paper performs a diagnostic test for the fixed-effect model, which focuses on the disturbance term of the regression. The result shows that groupwise heteroskedasticity and cross-sectional independence exist in the disturbance term. Therefore, this paper adopts “xtreg” in Stata 15 based on the result of the diagnostic test to correct the standard errors in the model:

\[
Air_{it} = \alpha_0 + \alpha_1 Recovery_{ij} + \alpha_2 Temperature_{it} + \alpha_3 Pressure_{it} + \alpha_4 Rain_{it} + \alpha_5 Heating_{it} + \delta Date_{it} + \mu_i + \epsilon_{it}
\]  

(4)

Cities and provinces included in this paper are listed in Table A.5.
and

\[
\log(\text{Air}_{i,t}) = a_0 + a_1 \text{Recovery}_{i,t} + a_2 \text{Temperature}_{i,t} + a_3 \text{Pressure}_{i,t} \\
+ a_4 \text{Rain}_{i,t} + a_5 \text{Heating}_{i,t} + \text{date}_t + \epsilon_i + \epsilon_{i,t}.
\]  

(5)

In Eqs. (4) and (5), the dependent variables are \(\text{Air}_{i,t}\) and \(\log(\text{Air}_{i,t})\). \(\text{Air}_{i,t}\) is air quality in city \(i\) on date \(t\), which is quantified by the concentration of PM2.5, SO2, and NOx. \(\log(\text{Air}_{i,t})\) is the natural logarithm of \(\text{Air}_{i,t}\). For the independent variable, \(\text{Recovery}_{i,t}\) is the recovery index constructed in this paper, which quantifies the degree of recovery during the period of easing COVID-19 restrictions. Moreover, we add four control variables in the regression, three of which are meteorological variables to control the impact of local weather conditions on air pollution. \(\text{Temperature}_{i,t}\) is the average temperature in city \(i\) on date \(t\), \(\text{Pressure}_{i,t}\) is air pressure at the height of 2 m above the ground in city \(i\) on date \(t\), and \(\text{Rain}_{i,t}\) is the amount of rainfall in city \(i\) on date \(t\). \(\text{Heating}_{i,t}\) is an important control variable for air quality, which is a dummy variable in this paper. \(\text{Heating}_{i,t}\) equals 1 if cities have collective winter heating, and when days are during the heating period in 2020; otherwise, \(\text{Heating}_{i,t}\) equals 0. The date-fixed effect \(\text{date}_t\), and city-fixed effect \(\epsilon_i\) are added to Eqs. (4) and (5) to absorb unobserved date- and city-specific effects.

2.2.3. Counterfactual analysis

To reflect the degree of changes in air quality during the recovery process, we construct the “virtual difference” of air pollution by subtracting the estimated counterfactual air quality \(\text{Air}_{i,t}^{\text{BAU}}\) from actual quality \(\text{Air}_{i,t}\). The variable of “virtual difference” in this paper is called “delta”.

We use the counterfactual framework (Eskander and Fankhauser, 2020) as a basis in using the statistical relationship in Eq. (4) to construct Eqs. (6) and (7) and calculate the counterfactual air quality \(\text{Air}_{i,t}^{\text{BAU}}\), which reflects what air quality would have been in the absence of COVID-19 in 2020. Moreover, the baseline level of recovery index is used in the counterfactual framework. Fig. 1 Panel (b) shows that the recovery index between \text{Baseline}_\text{Jan2020}, (i.e., level in January 2020 before COVID-19) and 100 % (i.e., level on the same day in 2019) is regarded as the baseline level of recovery index.

Fig. (6) uses \text{Baseline}_\text{Jan2020}, as the baseline level of recovery index, which is the average recovery index of city \(i\) on weekdays in the second and third weeks before Spring Festival. Hence \(\text{Air}_{i,t}^{\text{BAU}}\) can be expressed as follows:

\[
\begin{align*}
\text{Air}_{i,t}^{\text{BAU}} &= \hat{a}_0 + \hat{a}_1 \times \text{Baseline}_\text{Jan2020}, \\
+ &\hat{a}_2 \text{Temperature}_{i,t} + \hat{a}_3 \text{Pressure}_{i,t} + \hat{a}_4 \text{Rain}_{i,t} \\
+ &\hat{a}_5 \text{Heating}_{i,t} + \text{date}_t + \mu_i + \hat{\epsilon}_{i,t}.
\end{align*}
\]

(6)

Eq. (7) uses 100 % as the baseline level of recovery index, which means the relative migration level in certain city has returned to the level of the same date in 2019. The new \(\text{Air}_{i,t}^{\text{BAU}}\) can be written as follows:

\[
\begin{align*}
\text{Air}_{i,t}^{\text{BAU}} &= \hat{a}_0 + \hat{a}_1 \times 100 + \hat{a}_2 \text{Temperature}_{i,t} + \hat{a}_3 \text{Pressure}_{i,t} \\
+ &\hat{a}_4 \text{Rain}_{i,t} + \hat{a}_5 \text{Heating}_{i,t} + \text{date}_t + \mu_i + \hat{\epsilon}_{i,t}.
\end{align*}
\]

(7)

On the basis of the actual control variables and fixed effects in 2020, the constructed \(\text{Air}_{i,t}^{\text{BAU}}\) does not need to consider the improvement of air quality induced by policies for controlling air pollution over the past few years and also uses meteorological variables on the same date. Hence, this counterfactual framework solves the problems that previous empirical studies have assumed (i.e., pollutant levels in 2020 have not changed over the past few years) and disregarded (i.e., meteorological differences).

Therefore, air pollution’s “virtual difference” \(\text{delta}_{i,t}\) of city \(i\) on date \(t\) is expressed as follows:

\[
\text{delta}_{i,t} = \text{Air}_{i,t} - \text{Air}_{i,t}^{\text{BAU}}
\]

(8)

In this form, \(\text{delta}_{i,t}\) quantifies the extent to which actual air pollution is better or worse than the counterfactual air pollution without COVID-19, thereby reflecting the degree of improvement or deterioration in air quality during the recovery process in city \(i\) on date \(t\). When \(\text{delta}_{i,t}\) is less (more) than 0, \(\text{Air}_{i,t}\) is less (more) than \(\text{Air}_{i,t}^{\text{BAU}}\). Hence, actual air quality is better (worse) than the counterfactual air quality in city \(i\) on date \(t\). When \(\text{delta}_{i,t}\) equals 0, actual air quality is consistent with the counterfactual air quality without COVID-19.

2.2.4. Time series clustering based on wavelet transform

This paper uses time series clustering based on wavelet transform for the daily “virtual differences” of air pollution in 17 provinces (i.e., 17 time series data) to cluster them into different groups, which could be defined as different recovery modes, and analyze the underlying mechanisms.

Unlike cross-sectional data, time series data are simultaneously characterized by fluctuation and trend, and the interdependence relationship
between values also cannot be disregarded. Hence, time series clustering contains three steps: extracting trend and cleaning noise, measuring dissimilarity, and clustering time series based on dissimilarity (for details, see supplementary materials). The number of clusters can be chosen from the hierarchical tree (Fig. A.1).

3. Results

3.1. Descriptive statistics

Table 1 presents the descriptive statistics and Pearson correlation matrix for regression variables. It shows that PM$_{2.5}$ and NO$_2$ have similar mean values, which are about 26.8 $\mu g/m^3$ and 25.5 $\mu g/m^3$, respectively. However, the maximum value of PM$_{2.5}$ is about eight times higher than the counterpart of NO$_2$. Moreover, the mean value of the recovery index is 89.9 %, which indicates that the average recovery ratio of 119 cities from March to October 2020 reaches nearly 90 %. The highest daily recovery index peaks at 135.1 %, showing that the relative mobility situation on that day is about 1.35 times as large as the same day in 2019. For weather conditions, three meteorological variables have large differences between their maximum and minimum owing to seasonal and geographical heterogeneity. For example, the mean value of rain is about 4.1 mm, while the largest rain amount reaches 216.1 mm. For the correlation matrix, the recovery index has significant positive impacts on three air pollution components. Heating is positively related to air pollution, and rain has negative associations with PM$_{2.5}$, SO$_2$, and NO$_2$.

According to the construction method and line graph in Fig. 1, complete recovery does not mean that the recovery index needs to reach 100 %. Owing to normal fluctuations of human mobility between years, the recovery index in a specific range could be regarded as a complete recovery. Fig. 1 Panel (b) shows that the baseline level in January 2020 before the COVID-19 pandemic was only 91.4 %. Hence, the recovery index between 91.4 % and 100 % could be regarded as the range of full recovery. In March 2020, the average recovery index of 119 cities recovered from 63 % to over 90 %. The highest average recovery index was 106.9 % in April. That is, the relative inter-city inflow ratio in 2020 was about 1.07 times as high as the level on the same day in 2019. The rapid increase of recovery index in March and April 2020 may be attributed to COVID-19. On the one hand, the time for work resumption was delayed in the first quarter of 2020. On the other hand, it may be due to the prosperity of inter-city business during the economic recovery. In September and October 2020, the average recovery index stabilized at approximately 91.4 %, which nearly returned to the pre-pandemic level.

3.2. Impact of recovery on air pollution

3.2.1. Baseline estimation

Table 2 shows that the recovery index has a significant positive impact on air pollution. This paper uses the constructed recovery index and a fixed-effect model to estimate Eqs. (4) and (5). Coefficient $\hat{q}_1$ in Table 2 column (2) means that when the recovery level had a growth of 10 %, the concentration of PM$_{2.5}$, SO$_2$, and NO$_2$ deteriorated by 1.10, 0.33, and 1.25 $\mu g/m^3$, respectively. Table 2 columns (3) and (4) further discuss the impact of recovery on the average growth rate of air pollution. It shows a 3 %-6 % rebound in air pollution when the recovery level increased by 10 %. A similar conclusion could be seen between the recovery index and AQI in Table A.2.

The relationship between recovery and air pollution suggests that the recovery process has resulted in a rebound in air pollution during the period of easing COVID-19 restrictions. Given that the first wave of COVID-19 in China is gradually under control, lifting traffic restrictions is the signal to unlock cities, increase human mobility, and accelerate economic recovery. Therefore, when the recovery index increases, it increases the operating rate of enterprises by stimulating inter-provincial or inter-city labor migration and also facilitates commercial intercourse among enterprises situated in different places. Given that the economic activities of some high-emission industries are leading contributors to air pollution (Magazzino et al., 2022; Mele et al., 2021), the recovery process relatively increases cities’ air pollution.

On the other hand, the heterogeneous estimation results for three different air pollutants show that the recovery process has a larger impact on NO$_2$ and PM$_{2.5}$, but gives the least influence on SO$_2$. As a major pollutant associated with vehicles’ combustion of fossil fuels, NO$_2$ is one of the indicators of traffic pollution (Elsaid et al., 2021). Hence, when traffic restrictions are lifted and the recovery ratio starts to increase, NO$_2$ concentration experiences the strongest growth. Apart from transportation-related activities, recovery is also one of the important factors indirectly improving work resumption and the operating rate of heavy industrial activities (Ethan et al., 2022). Given that particulate pollution is a major pollutant in enterprises, the concentration of PM$_{2.5}$ receives the second largest impact from recovery.

This preceding result quantifies the recovery–air pollution nexus from the perspective of empirical analysis. Unlike Zheng (2022), who found no

| Table 1 |
|---|
| Descriptive statistics and Pearson correlation matrix. |
| Variable | Observation | Mean | Std. Dev. | Min | Max | PM$_{2.5}$ | SO$_2$ | NO$_2$ | AQI | Recovery | Temperature | Pressure | Rain |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| PM$_{2.5}$ ($\mu g/m^3$) | 17,822 | 26.782 | 18.898 | 2 | 984 | 1.000 | | | | | | | |
| SO$_2$ ($\mu g/m^3$) | 17,822 | 9.141 | 5.956 | 1 | 263 | 0.363*** | 1.000 | | | | | | |
| NO$_2$ ($\mu g/m^3$) | 17,822 | 25.536 | 12.605 | 2 | 112 | 0.530*** | 0.418*** | 1.000 | | | | | |
| AQI | 17,822 | 88.915 | 17.436 | 24.31 | 135.114 | 0.079*** | 0.165*** | 0.270*** | 0.175*** | 1.000 | | |
| Recovery (%) | 17,822 | 88.915 | 17.436 | 24.31 | 135.114 | 0.079*** | 0.165*** | 0.270*** | 0.175*** | 1.000 | | |
| Temperature (°C) | 17,822 | 20.555 | 7.297 | −10.490 | 33.200 | −0.237*** | −0.213*** | −0.293*** | 0.070*** | −0.056*** | 1.000 | | |
| Pressure (hPa) | 17,822 | 1011.285 | 7.811 | 754.625 | 1033.800 | 0.220*** | 0.120*** | 0.326*** | −0.076*** | 0.071*** | −0.686*** | 1.000 | |
| Rain (mm) | 17,822 | 4.109 | 10.969 | 0.000 | 216.100 | −0.180*** | −0.177*** | −0.166*** | −0.256*** | −0.126*** | 0.109*** | −0.192*** | 1.000 | |
| Heating | 17,822 | 0.070 | 0.256 | 0 | 1 | 0.171*** | 0.194*** | 0.085*** | 0.011 | −0.004 | −0.534*** | 0.270*** | −0.094*** | |

Note: *** and ** are statistically significant at the 1 %, 5 % and 10 % levels, respectively.

| Table 2 |
|---|
| Impact of recovery on air pollution. |
| Levels | Log |
|---|---|---|---|---|
| Panel A: PM$_{2.5}$ |
| Recovery | 0.132*** | 0.110*** | 0.004*** | 0.003*** |
| (0.034) | (0.028) | (0.001) | (0.001) |
| Panel B: SO$_2$ |
| Recovery | 0.038*** | 0.033*** | 0.004*** | 0.003*** |
| (0.007) | (0.006) | (0.001) | (0.001) |
| Panel C: NO$_2$ |
| Recovery | 0.147*** | 0.125*** | 0.006*** | 0.005*** |
| (0.024) | (0.017) | (0.001) | (0.001) |
| Control variables |
| N | Y | N | Y |
| City fixed effects |
| Y | Y | Y | Y |
| Date |
| Y | Y | Y | Y |
| Number of cities | 119 | 119 | 119 | 119 |
| Observations | 17,822 | 17,822 | 17,822 | 17,822 |

Note: (1) Panel-corrected standard errors are shown in parentheses. (2) *** and ** are statistically significant at the 1 %, 5 % and 10 % levels.
significant relationship between post-COVID-19 work resumption and regional air pollution for five provinces with relatively good air quality in Southern China in March–April 2020, the current study extends the sample to 119 key cities from March to October 2020, directly constructs a recovery index based on human mobility, and confirms that recovery has a significant positive impact on air pollution rebound.

3.2.2. Robustness check for reasonability of the constructed recovery index

To explain the reasonability of the recovery index constructed in this paper, we quantify the impact of lockdown measures on air quality by using the dataset during the lockdown period from January 4 to February 12, 2020 (see Table 3). Given that a number of empirical studies have discussed the impact of lockdown on air pollution, the result of the robustness could be more comparable with previous literature. Meanwhile, we rename the “recovery index” to “migration level” because this period is before and after the outbreak of COVID-19 rather than the recovery process. Moreover, the inclusion of Spring Festival in this dataset prompts us to adopt the same lunar period in 2019 as a benchmark, and construct Migration level following Eq. (1).

On the basis of the previously constructed migration level, we quantify the impact of migration level on air quality under the COVID-19 lockdown policies. The results in Table 3 columns (2) and (4) show that when migration levels reduced by 10%, PM2.5, SO2, and NO2 have respectively brought down by 2.99 points (3%), 0.19 points (1%), and 1.41 points (6%). Having dropped the peak period of spring festival travel rush (i.e., from the sixth day before the Chinese New Year in 2020 to the day before lockdown), the improvement of air quality was 2.58 points for PM2.5 and 2.70 for NO2 when the migration level reduced by 10%. The impact of migration level on AQI from January 4 to February 12, 2020 could be seen in Table A.3. These results are similar to previous studies (He et al., 2020; Bao and Zhang, 2020; Liu et al., 2020a; Wang et al., 2021a; Wang et al., 2021c; Zeng and Bao, 2021).

To make the estimated coefficients in Table 3 comparable with previous studies listed in Table A.4, we define lockdown based on travel restrictions (Bao and Zhang, 2020). Hence, the day when migration level dropped rapidly is defined as the first day receiving traffic restrictions and lockdown measures. The lockdown start dates for 119 cities are shown in Table A.5. Taking the sub-sample dropping the peak period of spring festival travel rush as an example, we calculate the average migration level before and after the COVID-19 lockdown policies, which are 91.5% and 18.8%, respectively. Therefore, the coefficients quantifying the impact of lockdown on air quality are −18.757 (=18.8% × 0.258−91.5% × 0.258) and −0.145 (=18.8% × 0.002−91.5% × 0.002) for PM2.5, −2.036 and −0.073 for SO2, −19.629 and −0.654 for NO2 based on the results in Table 3 columns (6) and (8). For PM2.5, the coefficients of −18.757 and −0.145 are near the coefficients in He et al. (2020) and Liu et al. (2020a), −0.073 (i.e., the coefficient for the regression of log(SO2) on lockdown) is in the reasonable interval between Bao and Zhang (2020) and Wang et al. (2021a) listed in Table A.4. The coefficient for the regression of log(NO2) on lockdown in Table 3 is near the coefficient in Wang et al. (2021a).

Hence, the constructed index could also have similar meanings when studying the lockdown period. That is, the recovery index constructed in this paper is reasonable.

3.2.3. Robustness check for measurement error

Given that the key explanatory variable “recovery” is a proxy variable constructed in this paper to quantify the real extent of recovery, it could have a relative measurement error. Hence, we conduct a robustness check by performing the two-stage least squares (2SLS) regression to tackle the measurement error.

Recovery lag is adopted as the instrumental variable, which is the recovery index with one-period lag. The first-stage regression result in Table 4 columns (1) shows that the instrumental variable Recovery lag is positively and significantly associated with Recovery when control variables are included. Columns (2)–(7) of Table 4 present the second-stage regression results, we observe that all coefficients of Recovery are positive and significant at the 1% level. Having compared the results mentioned above with Table 2, the coefficients and their meanings are quite similar. Moreover, we also conduct relevant tests to check the validity of the instrumental variable. As shown in Table 4, Cragg-Donald Wald F statistics are larger than Stock-Yogo weak ID test critical values, and Anderson-Rubin Wald tests are significant, thereby indicating that Recovery lag used in the first-stage is relatively free of weak identification problems. Meanwhile, on the basis of the endogeneity Chi-sq test of Recovery, the null hypothesis of exogeneity is rejected. Lastly, due to the equal number between the instrumental variable and endogenous variable, this regression is exactly identified. Hence, results of 2SLS confirm our main findings after dealing with the measurement error.

3.3. Five recovery modes based on the rebound in air pollution

Although we have quantified the impact of recovery on air pollution during the period of easing COVID-19 restrictions by constructing the recovery index and using the fixed-effect model, whether the rebound effect4 worsens or improves air quality compared with the counterfactual situation without COVID-19 remains unknown. Meanwhile, owing to different economic structures, regions’ major air pollutants could be heterogeneous. Hence, to reflect the degree of improvement or deterioration in air quality during the recovery process and make results comparable among regions, this paper uses AQI to represent air pollution and calculates the daily “virtual differences” (i.e., the difference between observed actual Air and estimated counterfactual Air BAU) of air pollution for 119 cities, which is based on the counterfactual framework (Eskander and Fankhauser, 2020). The variable of “virtual difference” in this paper is called “delta”.

Moreover, fluctuation of air pollution’s “virtual difference” during the period of easing COVID-19 restrictions is also an important reflection of the recovery process, which is dependent on regions’ industrial structure and resource endowments. Hence, we use time series clustering based on wavelet transform to classify the “virtual differences” of 17 provinces into five groups and define them into distinct recovery modes: energy-intensive, industrial-restructuring, policy-oriented, international trade-oriented, and less-impacting recovery modes5,6. Fig. 2 shows the geographical distribution of provinces in each recovery mode.

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4 The rebound effect in this paper is the rebound of actual air pollution resulted from recovery since the end of February 2020, i.e., the starting point of easing COVID-19 restrictions). However, what we are concerned about is not the absolute value of rebound effect but the net rebound gap. Hence, this paper constructs the “virtual difference” of air pollution in Section 2.2.3 to study whether the rebound has been more than or less than the counterfactual air pollution without COVID-19. If the “virtual difference” is more (less) than 0, it means that the rebound of air pollution is more (less) than the counterfactual air pollution without COVID-19, and the rebound effect has worsened (improved) air quality.

5 On the one hand, owing to the similarity in shape, “Shandong” needs to be grouped into the industrial-restructuring recovery mode, including Zhejiang and Jilin. A total of 17 time series are classified according to $d_{K2}(X_t,Y_t)$, which is a structure-based dissimilarity and relatively disregards the shape-based dissimilarity among time series (Montero and Vilar, 2014). Fig. A.2 shows that the shape of the reconstructed time series in Shandong is relatively similar to the shape of lines for Jilin and Zhejiang, particularly during the period with positive “virtual differences” of air pollution.

6 On the other hand, “Hubei & Beijing” and “Liaoning & Heilongjiang” need to be grouped together and called policy-oriented recovery mode. Although the shapes of time series between “Hubei & Beijing” and “Liaoning & Heilongjiang” are different, the two groups reflect regional policies for COVID-19 prevention and control in different phases. Beijing and Hubei are clustered owing to the similar trend during the first outbreak of COVID-19. As the capital of China and the first region severely affected by COVID-19, Beijing and Hubei imposed strict lockdown policies at the beginning of 2020. However, Liaoning and Heilongjiang are grouped because of similar fluctuations during the second and third local outbreaks of COVID-19 after May 2020. Although widespread COVID-19 have been controlled in this phase, there are still local infectious cases in some areas in China. Hence, Liaoning and Heilongjiang have similar policies to cope with regional outbreaks of COVID-19.
The compiled dataset is from January 4 to February 12, 2020, which is a short panel (N = 119, before and after the outbreak of COVID-19 rather than the recovery process. This allows us to determine whether the variable is endogenous or not.

Due to the exogenous shock of COVID-19 and weak development of other sectors, this recovery mode was dominated by resource-intensive industries. Owing to the exogenous shock of COVID-19 and weak development of other sectors, this recovery mode was dominated by resource-intensive industries. Owing to the exogenous shock of COVID-19 and weak development of other sectors, this recovery mode was dominated by resource-intensive industries. Owing to the exogenous shock of COVID-19 and weak development of other sectors, this recovery mode was dominated by resource-intensive industries. Owing to the exogenous shock of COVID-19 and weak development of other sectors, this recovery mode was dominated by resource-intensive industries. Owing to the exogenous shock of COVID-19 and weak development of other sectors, this recovery mode was dominated by resource-intensive industries. Owing to the exogenous shock of COVID-19 and weak development of other sectors, this recovery mode was dominated by resource-intensive industries. Owing to the exogenous shock of COVID-19 and weak development of other sectors, this recovery mode was dominated by resource-intensive industries. Owing to the exogenous shock of COVID-19 and weak development of other sectors, this recovery mode was dominated by resource-intensive industries. Owing to the exogenous shock of COVID-19 and weak development of other sectors, this recovery mode was dominated by resource-intensive industries. Owing to the exogenous shock of COVID-19 and weak development of other sectors, this recovery mode was dominated by resource-intensive industries. Owing to the exogenous shock of COVID-19 and weak development of other sectors, this recovery mode was dominated by resource-intensive industries. 

## Table 3

| January 4 to February 12, 2020 | Levels | Log | January 4 to February 12, 2020 | Levels | Log |
|-------------------------------|--------|-----|--------------------------------|--------|-----|
|                               |        |     |                                |        |     |
| Panel A: PM$_2.5$ Migration level | 0.339*** (0.039) | 0.299*** (0.038) | 0.004*** (0.000) | 0.003*** (0.000) | 0.317*** (0.049) | 0.258*** (0.048) | 0.003*** (0.001) | 0.002*** (0.001) |
| Panel B: SO$_2$ Migration level | 0.022*** (0.006) | 0.019*** (0.006) | 0.001*** (0.000) | 0.001*** (0.000) | 0.030*** (0.011) | 0.028*** (0.011) | 0.001*** (0.000) | 0.001*** (0.000) |
| Panel C: NO$_2$ Migration level | 0.147*** (0.012) | 0.141*** (0.012) | 0.006*** (0.000) | 0.006*** (0.000) | 0.274*** (0.019) | 0.270*** (0.018) | 0.009*** (0.001) | 0.009*** (0.001) |

Note: (1) The variable, Migration level, has a similar calculation method as the recovery index, reflecting the change of relative inter-city inflow ratio from January 4 to February 12, 2020 compared with 2019. We rename the “recovery index” to “migration level” because this period is before and after the outbreak of COVID-19 rather than the recovery process.

(2) The compiled dataset is from January 4 to February 12, 2020, which is a short panel (N = 119, T = 40).

(3) Columns (5)-(8) are based on the sample after dropping the peak period of spring festival travel rush, which starts from the sixth day before the Chinese New Year in 2020 to the day before lockdown.

(4) *** and * are statistically significant at the 1 %, 5 % and 10 % levels, respectively.

## Table 4

| First-stage | Second-stage |
|-------------|--------------|
| Recovery | PM$_2.5$ | log(PM$_2.5$) | SO$_2$ | log(SO$_2$) | NO$_2$ | log(NO$_2$) |
| (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Recovery | 0.134*** (0.011) | 0.004*** (0.000) | 0.039*** (0.003) | 0.004*** (0.000) | 0.149*** (0.007) | 0.006*** (0.000) |
| Recovery lag | 0.898*** (0.005) | 0.898*** (0.005) | 0.898*** (0.005) | 0.898*** (0.005) | 0.898*** (0.005) | 0.898*** (0.005) |
| Control variables | Y | Y | Y | Y | Y | Y |
| City fixed effects | Y | Y | Y | Y | Y | Y |
| Date | Y | Y | Y | Y | Y | Y |
| Number of cities | 119 | 119 | 119 | 119 | 119 | 119 |
| Observations | 4760 | 4760 | 4760 | 4760 | 4760 | 4760 |

Note: (1) Column (1) presents the first stage regression result of the relationship between Recovery and Recovery lag when control variables are included. Recovery lag is the instrumental variable which is the recovery index with one-period lag.

(2) Given that the number of instrumental variables is equal to the endogenous variable Recovery, this regression is exactly identified.

(3) Cragg-Donald Wald F statistic and Anderson-Rubin Wald F statistic are used to conduct weak identification test. Endogeneity Chi-sq test of Recovery tests whether the variable is endogenous or not.

(4) *** and * are statistically significant at the 1 %, 5 % and 10 % levels, respectively.
The policy-oriented recovery mode has regions with strong lockdown policies to cope with COVID-19, thereby resulting in slow economic recovery. Fig. 3 panel (c) shows that four regions in this mode had long-term negative “virtual differences” of air pollution during the recovery process. That is, these regions have not recovered to normal levels. The negative “virtual differences” in Beijing reflect the regional policies for prevention and control in the first and second outbreaks of COVID-19. Owing to the second outbreak in June, Beijing's strict policies made the “virtual differences” of air pollution go back to $-17$, thereby delaying the recovery progress. As the first region severely affected by COVID-19, Hubei experienced a two-phase unblocking process on March 25 and April 8, which could be seen through the rebound trajectory of “virtual differences” for air pollution. Moreover, the negative “virtual differences” in Liaoning and Heilongjiang were caused by lockdown policies to cope with the second or even third local outbreaks of COVID-19 after May 2020, thereby relatively affecting the level of regional recovery.

Regions in international trade-oriented recovery mode place international trade in an important position in the local economy. The recovery progress at the early stage was going well. However, the outbreak of COVID-19 in other countries and the closure of their borders and ports significantly affected China's international trade, particularly for regions in this mode. In Fig. 3 panel (d), their negative “virtual differences” of air pollution were between $-3$ and $-6$ after June 2020. In general, regions in this mode are in important economic circles in China (i.e., Jing-Jin-Ji region and Yangtze River Delta) and include two important ports in the north and south of China (i.e., Tianjin and Shanghai ports, respectively), thereby forming industrial clusters and are beneficial to international trade. However, the outbreak of COVID-19 in other countries hindered global logistics and blocked the upstream and downstream of the global industrial chain. This situation further resulted in an undesirable recovery process and made regions in the international trade-oriented recovery mode have lower economic performance than the level without COVID-19.

The less-impacting recovery mode has regions with a stable recovery process. These regions neither had the problem of a sharp rebound in air pollution nor needed to worry about the delay of the recovery process during the period of easing COVID-19 restrictions (Fig. 3 panel (e)). On the one hand, owing to industrial structure, geographical location, and policies for pollution control, some regions in this mode have had good air quality for numerous years (e.g., Guangdong). Thus, their recovery process had minimal impact on air quality. On the other hand, although there are energy-intensive industries in some regions of this mode (e.g., Ningxia and Gansu), these regions had fewer infectious cases of COVID-19 at the beginning of 2020. Thus, their recovery processes were relatively smooth and could prevent the sharp rebound of air pollution.

Compared with previous studies, some findings in this paper are mutually verified, while other results are different owing to heterogeneity in methods, baseline, and time series of the sample. In general, most provinces rapidly rebounded in March and April 2020 during the early stage of recovery, which is consistent with the findings of Zheng et al. (2020) and Liu et al. (2020b). However, for specific cities and provinces, this paper’s response level to the second wave of COVID-19 in Beijing is relatively larger than Tao et al. (2021). The reason is that the current research sets the “counterfactual air quality without COVID-19” as the benchmark. For Shanxi and Shaanxi, although both this paper and Zhang et al. (2020a) indicate that these two provinces have recovered to the normal level in March 2020, Zhang et al. (2020a) have not studied the retaliatory rebound of the two provinces in April 2020 owing to the limited time scale (February 10 to March 12, 2020). Lastly, because the spread of COVID-19 in other countries influences China's international trade after May 2020, regions in international trade-oriented recovery mode have not been identified by previous literature due to the limited time scale.

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For details, see “Supplementary Note 1: Detailed literature review” in the supplementary material.
4. Discussion

This study investigates how air pollution has rebounded after the first wave of COVID-19 in China. On the one hand, we construct a more representative dataset with 119 key cities, directly measure recovery by indices related to human mobility, and utilize the fixed-effect model to quantify the positive impact of recovery on air pollution. On the other hand, we further explore the degree of improvement or deterioration in air pollution compared with the counterfactual situation without COVID-19, and identify five heterogeneous recovery modes based on a counterfactual framework and time series clustering with wavelet transform. The result shows that energy-intensive and industrial-restructuring recovery modes have experienced a sharp rebound of air pollution during the recovery process. Influenced by policies for COVID-19 prevention and control and international trade blocks, policy-oriented and international trade-oriented recovery modes have not fully recovered to the level without COVID-19. Our findings have two important implications for long-term global green recovery.

Fig. 3. Five recovery modes on the basis of “virtual differences” for regional air pollution in China. The weekly “virtual difference” shown in this figure is called “delta”. Owing to different economic structures, regions’ major air pollutants could be heterogeneous. To make the “virtual difference” of each region comparable, this paper uses AQI as the comprehensive measure of actual air quality to calculate “delta”. The dotted line in this figure is the baseline level on the same day in 2019. The dashed line in this figure is the baseline level in January 2020 before COVID-19. Bootstrapped 95% confidence intervals are shown in shading areas.
The exogenous impact of COVID-19 has further intensified the differentiation of economic development and green recovery for regions in different recovery modes. For the energy-intensive recovery mode, COVID-19 has strengthened the position of resource-based and energy-intensive industries in the regional economy. Affected by their resource endowments and single industrial structure, regions cannot dispense with dependence on their traditional industries when they are exposed to an exogenous shock. Hence, achieving long-term green recovery is considerably challenging for them. However, regions in industrial-restructuring recovery mode have regarded the COVID-19 shock as an opportunity for industrial upgrading. Owing to the diversified industrial structure in such regions, the proportion of energy-intensive industries could be reduced by continuously increasing investments on technological innovation to facilitate the rapid development of high-tech manufacturing and tertiary industries. Hence, these regions can convert policy dividends during the period of easing COVID-19 restrictions into productivity and continuously improve the proportion of technology- and knowledge-intensive industries. Regions in industrial-restructuring recovery mode have strengthened the foundation for green recovery.

Although different recovery modes require heterogeneous effort and input to achieve green recovery, technological innovation, and industrial upgrading undeniably play important roles in all modes. Resource- and energy-intensive regions require the greatest effort to achieve green recovery by facilitating the development of equipment and high-tech manufacturing and diversifying the industrial structure. For economics relying on international trade, the exogenous impact of COVID-19 is a challenge and an opportunity for green recovery. Given that COVID-19 has resulted in a lock-in effect on the pattern of international trade, it raises the trade cost and reduces the comparative advantage of goods with low added value and high environmental impact. Hence, trade-oriented regions should bring their superiority of industrial clusters into full play. By process, product, functional, and inter-sectoral upgrading, these regions are able to enhance comparative advantages in the global value chains and trade commodities with lower environmental impact and higher added value (Humphrey and Schmitz, 2002). Lastly, regions with diversified industrial structures have stimulated the development of high-tech manufacturing and tertiary industries during the period of easing COVID-19 restrictions, which has an advantage in achieving long-term green recovery. In the future, such areas should further upgrade traditional manufacturing sectors and move toward intelligent manufacturing industries and a digital economy.

5. Conclusion and implications

As the second largest economy in the world, China is sparing no effort to recover from COVID-19, which has received global attention. By constructing the recovery index through human mobility and using the fixed-effect model, counterfactual framework, and time series clustering with wavelet transform, we draw the following conclusions from our empirical results. The recovery during the period of easing COVID-19 restrictions has resulted in a significant rebound of air pollution in China, and five recovery modes have been clustered and defined for 17 provinces in China.

This paper could have critical implications for policy makers in China and also in other countries to achieve economic transformation and strengthen the foundation for long-term green recovery. Generally speaking, technological innovation, digital transformation, upgrading in global value chains, and institutional innovation are common approaches to achieve green recovery. For regions strongly dependent on resource-based and energy-intensive industries, governments need to diversify regions’ industrial structure and reduce economic dependence on traditional industries with relatively high air pollution. On the one hand, it is necessary to introduce advanced technologies and extend the industry chain for traditional sectors, which could make those industries have less air pollution and produce products with higher added value. On the other hand, owing to the megatrend of digitalization and intelligent manufacturing, selecting and supporting manufacturing industries on the basis of regional conditions is conducive to cultivating new drivers of economic growth and promoting employment at the same time. For regions in industrial-restructuring recovery mode with diversified industrial structures, the proportion of technology- and knowledge-intensive industries should be improved. In response to the lock-in effect and green transformation on international trade, policymakers in trade-oriented regions are supposed to upgrade their industrial clusters to enhance comparative advantages of goods with low environmental impact and high added value in the global value chain. Lastly, governments in policy-oriented regions need to emphasize policy flexibility. Given that most lockdown policies relatively disregard economic development, policies aimed at economic recovery need to be flexibly imposed in an attempt to prevent the retaliatory rebound of air pollution and gradually facilitate green supply and demand at the same time.

This study has some possible limitations. On the one hand, this paper quantifies recovery based on indices related to human mobility, which is direct but relatively one-sided. Given that recovery is a comprehensive process that could be reflected in various aspects, further studies can improve the accuracy of the definition by measuring “recovery” from different angles. On the other hand, data limitations prevent us from examining the effects of recovery in countries with different institutions, development stages, and severity of COVID-19. Future research having access to such data can conduct a thorough comparison from a global perspective.

CRedIT authorship contribution statement

Xinyang Dong: Methodology, Data curation, Software, Formal analysis, Writing – original draft, Writing – review & editing. Xinzhu Zheng: Formal analysis, Data curation, Writing – original draft. Can Wang: Conceptualization, Supervision, Formal analysis, Writing – review & editing. Jinghai Zeng: Methodology, Data curation, Formal analysis. Lixiao Zhang: Investigation, Formal analysis.

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.

Acknowledgements

The authors acknowledge funding by the National Natural Science Foundation of China project (No. 71773062 and 71904201), the National Key Research and Development Program of China (2017YFA0603602), and State Key Joint Laboratory of Environmental Simulation and Pollution Control (17L02ESP). Appendix A. Supplementary materials

Supplementary materials to this article can be found online at https://doi.org/10.1016/j.scitotenv.2022.156942.

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