Threshold effects of COVID-19-confirmed cases on change in pollutants changes: evidence from the Chinese top ten cities

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Abstract

A more comprehensive understanding of the impact of the COVID-19 pandemic on changes in pollution could serve us to better deal with the environmental challenges caused by the pandemic. Existing studies mainly focused on the linear impact of the pandemic on the pollutants without considering the impact of other factors. To fill the research gap, the nonlinear relationship between pandemic and pollutants with considering the temperature factor was explored by developing panel threshold regression approach. In the proposed approach, the number of confirmed cases was set as explanatory variable, concentrations of NO₂ and PM_{2.5} were set as explained variables, temperature was used as threshold variable, and other air pollution indicators were used as control variables. The results showed that there is a threshold effect between the changes in confirmed COVID-19 cases and the concentrations of PM_{2.5} and NO₂, confirming the impact of the pandemic on pollutions was nonlinear. The results also show that the negative impact of pandemic on pollution increased when the temperature was rising. This work had theoretical and practical significance. The nonlinear research perspective of this article provided a methodological reference for exploring the relationship between epidemic and pollutant-related variables. Furthermore, this study expanded the scope of application of the threshold panel regression model and enriched the quantitative analysis of epidemics and pollutants.

Keywords Air pollutants · Nonlinear relationship · Temperature · COVID-19 · Panel data

Introduction

To curb the spread of COVID-19, governments of various countries have adopted a series of measures, such as restricting residents from going out, stopping bazaars and

gatherings, and suspending work and classes. Transportation and economic activities have dropped significantly, which has caused significant changes in the concentration of air pollutants. China has been facing the dilemma of environmental pollution (Dong and Liu 2020). Scholars were not only concerned about the impact of the weakening of economic activities caused by the control of the epidemic on the changes in pollutants but also the relationship between pollutants and COVID-19.

At present, many scholars have conducted research on the correlation between air quality and the spread of COVID-19. Zhu et al. (2020) collected panel data from 120 cities in China from January 23, 2020, to February 29, 2020, and applied a generalized additive model to study the correlation between six air pollutants and confirmed cases of COVID-19. Pei et al. (2020) used comparative analysis methods and used remote sensing and field observation data to analyze the impact of COVID-19 prevention and control on the atmospheric environment in Beijing, Wuhan, and Guangzhou in China. The results showed that the NO₂ concentration showed a downward trend across the country, but the change trend of PM_{2.5} concentration in different regions was obviously

Highlights

- The panel threshold regression approach was developed.
- Temperature was used as a threshold variable; other air pollution indicators were used as control variables.
- Negative nonlinear impact of pandemic on pollution increased when the temperature was rising.

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different. Lin et al. (2020) evaluated the impact of meteorological parameters and air quality in 29 provinces in China on the spread of COVID-19. The basic reproduction rate was calculated by the maximum likelihood removal method based on the chain binomial model, and the correlation between COVID-19 and atmospheric pollutants or meteorological parameters was estimated through correlation analysis. Saez et al. (2020) studied the effects of long-term exposure to air pollutants on the spread of COVID-19 and the risk of death in Catalonia, Spain. The method used in the article was a hybrid longitudinal ecological design and a generalized linear hybrid model. Domingo et al. (2020) assessed the potential relationship between the impact of air pollutant concentrations on the airborne transmission of SARS-CoV-2 and the severity of the COVID-19 coronavirus infection. Research results showed that long-term exposure to certain air pollutants can lead to more serious coronavirus infections and more difficult recovery. Berman and Ebisu (2020) assessed the air quality during the COVID-19 pandemic in the continental United States from January 8, 2017, to April 21, 2020. The county-level pollution concentration during the historical period and the new crown pneumonia period was compared. Chen et al. (2020) used the attribution score method to estimate the daily specific cause-of-death mortality that China avoided during mass quarantine due to reduced air pollution. Le et al. (2020) found that during the outbreak of China's new crown pneumonia, air pollution was abnormal, and air pollution was alleviated. Wang et al. (2020) used the community multi-scale air quality model from January 1 to February 12, 2020, to study the changes in PM_{2.5} in 10 cities in China under the emission reduction scenario after the "blocking the city" of the epidemic. Wu et al. (2020) investigated the number of COVID-19 deaths in more than 3000 counties in the USA and the county-level PM_{2.5} long-term average, fitted a negative binomial mixed model, and performed more than 68 additional sensitivity analyses. It was found that with an increase of $1\mu\text{g}/\text{m}^3\text{PM}_{2.5}$, the COVID-19 mortality rate increased by 8%. He et al. (2020) inferred the short-term impact of COVID-19 on air pollution in Chinese cities and used the difference model in difference to compare cities with and without lockdown policies. It was found that the city blockade had made a considerable improvement in air quality. Fattorini and Regoli (2020) collected actual COVID-19 data and corresponding long-term air quality assessments in various Italian provinces and elaborated and tested the interaction between them. Zhang et al. (2020) used the data of newly confirmed cases in 219 cities in China from January 24 to February 29, 2020, to study the impact of weather conditions and air pollution as co-factors on the spread of COVID-19. Contini and Costabile (2020) found that exposure to air pollution can increase vulnerability and adversely affect the prognosis of COVID-19 patients. Shehzad et al. (2020) discussed the effectiveness of COVID-19 on air pollution in Indian territory

from January to April 2020. By implementing an artificial neural network model, Magazzino et al. (2020) estimated a precise point in the neural transmission from PM₁₀ and PM_{2.5} to the number of deaths due to COVID-19 in the three cities of Paris, Lyon, and Marseille in France. This point would describe the predictable concentration of particulate matter, which would lead to an increase in the number of deaths due to COVID-19. Singh et al. (2020) estimated the changes in six standard air pollutants during the national lockdown in India caused by the COVID-19 pandemic. Comunian et al. (2020) analyzed the role of Italian particulate matter in the spread and increase of COVID-19 morbidity and mortality. Gupta et al. (2020) used statistical methods such as analysis of variance and regression models to analyze the relevant data of nine Asian cities and found that air pollution is a basic and hidden factor that increases the global burden of COVID-19-related deaths. Copat et al. (2020) systematically reviewed the literature on the relationship between some atmospheric pollutants (PM_{2.5}, PM₁₀, NO₂) and the spread and mortality of COVID-19. Cole et al. (2020b) estimated the relationship between long-term air pollution exposure and COVID-19 in 355 municipalities in the Netherlands. Hendryx and Luo (2020) tested the relationship between long-term exposure to air pollutants, possible pollution sources, and the prevalence and mortality of COVID-19 in the USA as of May 31, 2020, through linear multiple regression analysis with mixed models. Adams (2020) assessed the air pollution response in Ontario, Canada, during the COVID-19 emergency. Benmarhnia (2020) discussed the methodological challenges and opportunities for the link between air pollution and COVID-19, focusing on the role of air pollution as an influence modifier in the temporal and spatial variability of disease transmission and changes in the severity of symptoms and mortality. The indirect impact of interventions to control the human-to-human transmission of new coronary pneumonia on air pollution and population health was also considered. Xiang et al. (2020) assessed the impact of COVID-19 on traffic-related air pollution in cities in the northwestern United States and used a multiple autoregressive model to make comprehensive adjustments to weather. Cole et al. (2020a) used a two-step method to quantify the impact of Wuhan's new crown pneumonia epidemic prevention and control on the concentration of four air pollutants. First, machine learning is used to eliminate the confounding effects of weather conditions on pollution levels. Second, a new enhanced integrated control method is used to estimate the impact of the blockade on weather normalization pollution relative to a group of cities that are not blocked. Urrutia-Pereira et al. (2020) compiled environmental data released by multiple data centers and discussed the impact of the new crown pneumonia epidemic on environmental pollution. Azuma et al. (2020) conducted a longitudinal cohort study on the potential relationship between the spread of COVID-19 infection and climate or ambient air pollution in 28 regions of Japan. Son et al. (2020) investigated the impact of COVID-19

mitigation measures on air pollution levels in ten US states and the District of Columbia and subsequent decline in mortality. Frank et al. (2020) evaluated the impact of ozone on crops during COVID-19 through improved models and methods and believed that the unprecedented and unexpected drop in air pollutant emissions may lead to a decrease in seasonal ozone concentration and have a positive impact on crop yields. Through the analysis of short-term and long-term drivers of carbon emissions, Wang and Wang (2020b) discussed how to prevent the retaliatory growth of carbon emissions after COVID-19.

Through literature review, we found that the current research had the following gaps. Although the relationship between COVID-19 and air pollutants has been discussed in many existing literatures, the current studies have focused more on the linear impact of the epidemic on air pollutants. The existing literatures involved many applications of linear models but only considered the direct effects between variables. There were few studies on the indirect influence of a factor on the relationship between variables. Thus, the queries were raised: Is there a nonlinear relationship between COVID-19 and air pollutants? Is there a factor that has significant impact on the relationship between these two variables?

In order to cover the abovementioned gaps, this article had the following contributions. First, this article provided a new research perspective, based on the threshold panel regression model, to explore the nonlinear relationship between COVID-19-confirmed cases and air pollution in the top ten cities in China's GDP. Second, a new variable "temperature" was added to observe the indirect influence of this factor on the relationship between COVID-19 and air pollutants.

Regarding remains of this paper, "Research methods and data sources" section introduced the research methods and data sources. "Empirical results and discussion" section analyzed the data calculation results. "Conclusion" section drew conclusions and put forward some specific questions and recommendations for public policy makers to consider when discussing COVID-19 and environmental issues.

Research methods and data sources

Single threshold regression model

Threshold panel regression model was usually used to study the nonlinear relationship between multiple variables (Wang and Wang 2021a). This paper selected the Hansen threshold regression model (Hansen 1999) for econometric analysis. The research objects were the top ten cities in China's GDP. It mainly explored whether there is a nonlinear relationship between confirmed cases and air pollutants at different stages of threshold variables.

Model construction

$$y_{i,t} = \beta_0 Z_{it} + \beta_1 R_{it} I(q_{it} \leq \gamma) + \beta_2 R_{it} I(q_{it} > \gamma) + \mu_i + \varepsilon_{i,t} \quad (1)$$

where i represents the city and t represents the date. $y_{i,t}$ is the indicator value of a certain air pollutant in city i at time t , which is the explained variable. q_{it} is the threshold variable. R_{it} is the core explanatory variable affected by the threshold variable, that is, the number of confirmed cases in city i at time t . Z_{it} is the variable that has significant impact on the air pollutant except for confirmed cases. β_0 , β_1 and β_2 are corresponding coefficients, and γ is specific threshold value. $I(\cdot)$ is an indicative function, and the value in the corresponding brackets is 1 when the condition is satisfied and 0 when the condition is not satisfied. μ_i is the individual effect, and $\varepsilon_{i,t}$ is random interference term. Equation (1) can also be expressed as follows:

$$y_{i,t} = \beta_0 Z_{it} + \beta R_{it}(q_{it}, \gamma) + \mu_i + \varepsilon_{i,t} \quad (2)$$

$$R_{it}(q_{it}, \gamma) = \begin{cases} R_{it} I(q_{it} \leq \gamma) \\ R_{it} I(q_{it} > \gamma) \end{cases}$$

Model estimation and testing

Hansen believed that three issues need to be paid attention to. ① Estimate the threshold value. ② Test whether the threshold effect exists. ③ Test whether the threshold value is equal to the true value.

Estimate the threshold value.

Hansen proposed to use the two-stage least squares method to estimate the threshold panel model. Calculate the corresponding residual sum of squares for given threshold value, and then the threshold corresponding to the minimum value of all residual square sums is the threshold estimated value. The individual effect needs to be eliminated before model estimation (Wang and Wang 2021b). All cross sections of Eq. (1) are averaged within the group to obtain Eq. (3).

$$y_{i,t}^* = \beta_0 Z_{i,t}^* + \beta_1 R_{i,t}^* I(q_{it} \leq \gamma) + \beta_2 R_{i,t}^* I(q_{it} > \gamma) + \varepsilon_{i,t}^* \quad (3)$$

The observations are stacked, and they are expressed as:

$$y^* = R^*(\gamma) \beta + \varepsilon^* \quad (4)$$

Therefore, for a given threshold value γ , the least square estimation of explanatory variable coefficients can be expressed as:

$$\hat{\beta}(\gamma) = \{R^*(\gamma)' R^*(\gamma)\}^{-1} \{R^*(\gamma)' y^*\} \quad (5)$$

The residual sum of squares is:

$$S(\gamma) = \hat{\varepsilon}^* (\gamma)' \hat{\varepsilon}^* (\gamma) \quad (6)$$

The least squares estimate of the threshold γ is $\hat{\gamma} = \arg \min \text{SSE}(\gamma)$. The arg min function represents the set of γ corresponding to when the residual sum of squares is the smallest. The estimated residual vector is $\hat{\varepsilon}^* = \hat{\varepsilon}^*(\hat{\gamma}) = y^* - R^*(\gamma)\beta$, the estimated residual variance is $\hat{\sigma}^2 = \varepsilon^* \varepsilon^* / N(T-1) = S(\hat{\sigma}) / N(T-1)$, and estimated regression coefficient is $\hat{\beta} = \hat{\beta}(\hat{\gamma})$. T is the time span, and N is the number of sample cities.

Test whether the threshold effect exists.

Hansen proposed the Bootstrap method with consistent heteroscedasticity to obtain its asymptotic distribution and then constructed the P value and proved that the P value constructed by this method is gradual and effective.

The null hypothesis is that there is no threshold effect:

$$H_0 : \beta_1 = \beta_2 \quad (7)$$

The alternative hypothesis is:

$$H_1 : \beta_1 \neq \beta_2 \quad (8)$$

The F statistic for testing the null hypothesis is:

$$F_1 = \frac{S_0 - S_1(\hat{\gamma})}{\hat{\sigma}^2} \quad (9)$$

where S_0 and S_1 are the sum of squared residuals under the null hypothesis and alternative hypothesis, respectively. If the P value is less than the expected critical value, the null hypothesis H_0 is rejected; that is, there is a threshold effect; otherwise, the null hypothesis is accepted, and the model is a linear model.

③ Test whether the threshold value is equal to the true value.

Hansen pointed out that the best way to construct a confidence interval for γ is to construct a “non-rejection

domain” using likelihood ratio statistics. The null hypothesis is that the threshold value is equal to the true value, which can be expressed as $H_0 : \gamma = \gamma_0$. The likelihood ratio statistic is

$$LR(\gamma) = \frac{S_1(\gamma) - S_1(\hat{\gamma})}{\hat{\sigma}^2} \quad (10)$$

Among them, $S_1(\gamma)$ and $S_1(\hat{\gamma})$ are the sum of squared residuals of the null hypothesis and the alternative hypothesis, respectively. Hansen proved that $LR(\gamma)$ obeys a normal distribution. Assuming that $C(\alpha)$ is the non-rejection interval, $C(\alpha) = -2\ln(1 - \sqrt{1 - \alpha})$, α is the significance level, and the effective asymptotic confidence interval is estimated accordingly. If $LR(\gamma) > C(\alpha)$, reject the null hypothesis, and the threshold estimate is meaningless when the significance level is α . Otherwise, accept the null hypothesis; that is, when the significance level is α , the threshold estimate is meaningful.

Multi-threshold regression model

When it is determined that there is a threshold effect, it is necessary to continue to test whether there are two or more thresholds in the model. This article introduces the double threshold model, which is constructed as follows:

$$y_{i,t} = \beta_0 Z_{it} + \beta_1 R_{it} I(q_{it} \leq \gamma_1) + \beta_2 R_{it} I(\gamma_1 < q_{it} < \gamma_2) + \beta_3 R_{it} I(q_{it} \geq \gamma_2) + \mu_i + \varepsilon_{i,t} \quad (11)$$

where γ_1 and γ_2 are two threshold values and the corresponding coefficients are β_1 , β_2 and β_3 . When we know the first threshold estimated value $\hat{\gamma}_1$, search for the second threshold γ_2 . We arrive at:

$$S_2^*(\gamma_2) = \begin{cases} S(\hat{\gamma}_1, \gamma_2) & \text{if } \hat{\gamma}_1 < \gamma_2 \\ S(\gamma_2, \hat{\gamma}_1) & \text{if } \gamma_2 < \hat{\gamma}_1 \end{cases} \quad (12)$$

The second threshold estimated value is $\hat{\gamma}_2 = \arg \min S_2^*(\gamma_2)$. Next, we constructed the F_2 statistic to test whether the single threshold or the double threshold is more significant.

Table 1 Variable description and data sources

Variable type	Variable name	Abbreviation	Unit	Data sources
Explanatory variable	Confirmed cases	conf	person	NHC (2020)
Explained variable 1	NO2	NO2	μg/m ³	China Air Quality (2020)
Explained variable 2	PM2.5	PM2.5	μg/m ³	
Control variable	PM10	PM10	μg/m ³	Temperature data (2020)
Control variable	SO2	SO2	μg/m ³	
Threshold variable	temperature	temp	°C	

Table 2 Descriptive analysis of variables

Variables	Obs	Mean	Sd	Min	Q1	Q2	Q3	Max
conf	840	4966.307	14000	2.000	166.000	362.000	559.500	50000
NO2	840	30.218	13.940	5.000	20.000	28.000	38.000	98.000
PM2.5	840	33.935	21.178	3.000	21.000	30.000	43.000	207.000
PM10	840	51.094	25.727	6.000	32.500	47.000	65.500	154.000
SO2	840	6.116	2.291	2.000	5.000	6.000	7.000	17.000
temp	840	13.703	5.759	-4.500	10.000	13.750	18.000	27.500

Obs is the observed value, Mean is the average, Sd is the standard deviation, Min is the minimum, Q1 is the first quartile, Q2 is the median, Q3 is the third quartile, and Max is the maximum

$$F_2 = \frac{S_1(\hat{\gamma}_1) - S_2^\gamma(\hat{\gamma}_2^\gamma)}{\hat{\sigma}^2} \quad (13)$$

It is an approximate likelihood ratio test. Wang and Wang (2020a) also agree with this point. If the value of F_2 is larger, then we reject the null hypothesis; that is, the double threshold effect is more significant.

Variable selection and data source

On January 30, 2020, the World Health Organization announced that COVID-19 was listed as a public health emergency of international concern. Therefore, the data in this article was for the time span of January 30 to April 22 (84 days). This article used the top ten cities in China's GDP ranking (Shanghai, Beijing, Shenzhen, Guangzhou, Chongqing, Suzhou, Wuhan, Chengdu, Hangzhou, Tianjin) from January 30 to April 22,

2020, as a panel data sample to explore the nonlinear relationship between confirmed cases and air pollution. We collected daily air pollution indicators data, temperature data, and the number of confirmed cases in 10 cities during the study period. We chose temperature as the threshold variable, the number of confirmed cases as the explanatory variable, NO2 and PM2.5 as the explained variables, and other air pollution indicators as the control variables. The variable description and data sources are shown in Table 1.

Empirical results and discussion

Data descriptive analysis

Based on the collected data, this article selected January 30 to April 22, 2020, as the sample interval, and the cross section was the top 10 cities in China's GDP. Each variable contained 840 pieces of data. The

Table 3 Unit root test of panel data

Variables		conf	NO2	PM2.5	PM10	SO2	temp
Testing method		Augmented Dickey-Fuller (ADF)					
At level	t-Statistic	-1.9673	-6.9808	-13.6551	-14.3751	-7.2565	-6.9085
	Prob.	0.3015	0.0000	0.0000	0.0000	0.0000	0.0000
	Stability	No	Yes	Yes	Yes	Yes	Yes
At 1st difference	t-Statistic	-27.9134	-18.3193	-18.3145	-11.5258	-18.6071	-20.4174
	Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Stability	Yes	Yes	Yes	Yes	Yes	Yes
Testing method		Phillips-Perron (PP)					
At level	t-Statistic	-2.2688	-14.376	-13.7901	-14.6036	-15.0988	-6.9085
	Prob.	0.1825	0.0000	0.0000	0.0000	0.0000	0.0000
	Stability	No	Yes	Yes	Yes	Yes	Yes
At 1st difference	t-Statistic	-28.1026	-115.212	-98.6298	-127.563	-126.491	-37.8955
	Prob.	0.0000	0.0001	0.0001	0.0001	0.0001	0
	Stability	Yes	Yes	Yes	Yes	Yes	Yes

Table 4 Test results of threshold effect

Model	<i>F</i> -value	<i>P</i> -value	Number of Bootstrap	Critical value		
				1%	5%	10%
Single threshold	18.451*	0.062	500	25.736	19.698	13.827
Double threshold	0.016	0.874	500	2.295	1.886	1.426
Triple threshold	2.256	0.290	300	6.074	4.864	4.090

***, **, and * represent significance at the significance level of 1%, 5%, and 10% respectively

variables were confirmed cases (conf), NO₂, PM_{2.5}, PM₁₀, SO₂, and temperature (temp). The descriptive statistical results of the sample data are shown in Table 2. It can be seen that the standard deviation of confirmed cases in each city was relatively large, indicating that the spread of the epidemic in each city varied greatly. In addition, the degree of air pollution and temperature varied among cities.

Unit root test

Before constructing the model, it was necessary to test the stationarity of each variable, which is the unit root test of the variable. Only when each variable has passed the stationarity test can the next step be tested. The common unit root test methods were ADF test and PP test. This paper used these two testing methods to test the stationarity of six variables. According to whether the indicators have passed the 1% significance level as the test standard, the results are shown in Table 3. The results showed that all variables passed the tests of ADF and PP at 1st difference, indicating that these variables are stable. Therefore, the data can be tested for the next step of the panel threshold effect.

Panel threshold effect test and threshold value estimation

NO₂ as the explained variable

First, the temperature indicator was used as threshold variable to investigate the relationship between confirmed cases and

the concentration of NO₂ in the air. Before regressing the threshold model, first check whether the threshold effect exists. We used the Bootstrap method proposed by Hansen to test the threshold variables. We judged the threshold effect of confirmed cases on NO₂ concentration according to the tested *F* statistic and *P* value, and test whether there was a nonlinear relationship and the number of thresholds. The results are shown in Table 4. It can be seen that the *F* statistic in the single threshold model was 18.451, and the *P* value was 0.062. The null hypothesis was rejected at the 10% significance level, indicating that there was a single threshold value.

According to the above threshold effect test, a single threshold regression calculation was performed on the model. The estimated threshold is shown in Table 5 and Fig. 1. We can see that the threshold estimate obtained by the single threshold regression model was 19.5. The 95% confidence interval was [17.5, 20.0], the confidence interval was narrow, and the threshold estimate was credible.

In this paper, without adding threshold variables, the ordinary panel model was regressed, and the fixed effect model was used to obtain parameter estimates. We compared the regression results of the threshold effect model and the fixed effect model, as shown in Table 6.

The results showed that in the fixed effect model, the confirmed case had a negative effect on the NO₂ concentration with a coefficient of −0.00009. PM_{2.5} and NO₂ also showed a

Table 5 Estimated threshold value

Model	Estimated threshold value	95% confidence interval
Single threshold	19.5*	[17.5, 20.0]
Double threshold	21.5	[21.5, 22.5]
	19.5	[17.5, 20.0]
Triple threshold	10.0	[4.0, 21.5]

***, **, and * represent significance at the significance level of 1%, 5%, and 10% respectively

Fig. 1 Single threshold estimate

Table 6 Regression results of threshold model and fixed effect model

Variables	Threshold model (NO ₂)	Fixed effect model (NO ₂)
conf	--	−0.00009 (0.00007)
conf (temp≤19.5)	−0.00005 (0.00007)	--
conf (temp>19.5)	−0.00038*** (0.00010)	--
PM _{2.5}	−0.03434 (0.02742)	−0.02992 (0.02766)
PM ₁₀	0.22201*** (0.02610)	0.22710*** (0.02631)
SO ₂	2.89137*** (0.24411)	2.61465*** (0.23585)
Constant	2.81764** (1.27499)	4.10198*** (1.24366)

***, **, and * represent significance at the significance level of 1%, 5%, and 10% respectively. The content in parentheses is the standard deviation.

negative correlation with a coefficient of −0.02992. But the effect of these two variables was not significant. The positive effects of PM₁₀ and SO₂ were significant.

In the threshold regression model, the influence of explanatory variables on NO₂ concentration was also negatively correlated. When the temperature crossed the threshold, the negative effect of confirmed cases on NO₂ was strengthened. When the temperature was lower than 19.5°C, the number of confirmed cases increased by 1%, and the NO₂ concentration decreased by about 0.005%. When the temperature was higher than 19.5°C, the number of confirmed cases increased by 1%, and the NO₂ concentration decreased by approximately 0.038%. And when the temperature crossed the threshold, the significance of the negative correlation between variables was more obvious. Some scholars put forward many suggestions to protect the environment. Hua et al. (2021) believed that waste recycling behavior is a newly developing pro-environment behavior. More targeted measures are needed to reduce air pollution and protect the environment.

PM_{2.5} as the explained variable

Second, this article used temperature indicators as threshold variables to investigate the relationship between confirmed cases and PM_{2.5} concentrations in the air. We used the Bootstrap method proposed by Hansen to check whether the

Table 8 Estimated threshold value

Model	Estimated threshold value	95% confidence interval
Single threshold	20.5*	[4.0, 23.0]
Double threshold	21.5	[5.5, 22.5]
	20.5	[4.0, 22.5]
Triple threshold	14.0	[4.0, 22.5]

***, **, and * represent significance at the significance level of 1%, 5%, and 10% respectively

threshold effect exists. The test results are shown in Table 7. It can be seen that the F statistic in the single threshold model was 4.358, and the *P* value was 0.066. The null hypothesis was rejected at the 10% significance level, indicating that there was a single threshold value. Based on the threshold effect test, a single threshold regression was performed on the model. The threshold estimated value is shown in Table 8. The threshold estimated value obtained by the single threshold regression model was 20.5.

This paper used a fixed effect model to regress the ordinary panel model without adding threshold variables. We compared the parameter estimates of the threshold effect model and the fixed effect model, as shown in Table 9.

The results showed that in the fixed effect model, the impact of confirmed cases on PM_{2.5} concentration was negative, and it was highly significant at the 1% significance level. The calculated coefficient was −0.00035.

In the threshold regression model, the impact of confirmed cases on PM_{2.5} concentration also showed a highly significant negative correlation. When the temperature crossed the threshold, the negative effect of confirmed cases on PM_{2.5} was strengthened. When the temperature was lower than 20.5°C, the number of confirmed cases increased by 1%, and the PM_{2.5} concentration decreased by 0.033%. When the temperature was higher than 20.5°C, the number of confirmed cases increased by 1%, and the PM_{2.5} concentration decreased by 0.061%.

In summary, confirmed cases had a nonlinear effect on the NO₂ concentration and PM_{2.5} concentration in the air, and both showed a negative correlation. This result was not difficult to understand. In order to control the spread of the epidemic, the country had adopted an isolation policy of

Table 7 Test results of threshold effect

Model	F-value	P-value	Number of Bootstrap	Critical value		
				1%	5%	10%
Single threshold	4.358*	0.066	500	12.447	5.157	3.551
Double threshold	1.577	0.140	500	5.143	2.870	1.947
Triple threshold	1.744	0.310	300	28.841	13.840	8.607

***, **, and * represent significance at the significance level of 1%, 5%, and 10% respectively

Table 9 Regression results of threshold model and fixed effect model

Variables	Threshold model PM2.5	Fixed effect model PM2.5
conf	--	−0.00035*** (0.00010)
conf (temp≤20.5)	−0.00033*** (0.00010)	--
conf (temp>20.5)	−0.00061*** (0.00016)	--
PM10	0.68352*** (0.04037)	−0.05257 (0.04859)
SO2	−0.84462** (0.36089)	0.68311*** (0.02665)
NO2	−0.05238 (0.15104)	−0.83257** (0.33609)
Constant	7.49732*** (4.55919)	7.45232*** (1.63781)

***, **, and * represent significance at the significance level of 1%, 5%, and 10% respectively. The content in parentheses is the standard deviation.

“blocking the city.” The economic development of various cities was subject to certain restrictions, and the reduction of economic activities in various industries had led to a reduction in the emission of air pollutants. Furthermore, we found that when the threshold was crossed, the negative effects of confirmed cases on the concentration of NO₂ and PM2.5 in the air were significantly enhanced. Making reasonable policies was important to China’s environmental protection (Liu and Dong 2021).

Conclusion

This paper developed panel threshold regression approach to investigate the impact of COVID-19-confirmed cases on air pollution in the China’s top ten cities. The computing result showed that there is a nonlinear relationship between COVID-19 and air pollutants, and the temperature variable has a significant impact on the relationship between these two variables. The confirmed cases had a nonlinear effect on the NO₂ concentration in the air, showing a negative correlation. When the temperature crossed the threshold, the negative effect of confirmed cases on NO₂ was strengthened, and the significance of the negative correlation between the variables was more obvious. The impact of the confirmed disease on the PM2.5 concentration in the air also showed a highly significant negative correlation. When the temperature crossed the threshold, the negative effect of confirmed cases on PM2.5 was strengthened.

This research helps us clarify the relationship between human production and operation activities caused by COVID-19 and air pollution and provides richer information for future environmental policy design. Effectively controlling the epidemic and reducing the emission of air pollutants are issues that need to be focused on. Public policy makers need to prevent the retaliatory rebound of air pollutants based on the resumption of work and production in society. This article

suggests that in the short term, the stability of various industries can be controlled through corresponding incentives or subsidies, while in the long term, it is necessary to incorporate urban emission reduction technologies into local assessment targets to improve efficiency; include areas with inadequate implementation of comprehensive air pollution control tasks, prominent environmental problems, and obvious deterioration of ambient air quality into the central ecological environment protection inspection category; implement hierarchical and classified management and control of corporate performance, strengthen joint prevention and control, and continue to promote clean energy; and adhere to the problem orientation, compact the responsibilities of departments and localities, and increase assistance to prevent the rebound of heavy pollution.

This paper is conducted from a new perspective, considering the nonlinearity, and adding the temperature variable, which provides a methodological reference for studying the nonlinear relationship between the epidemic situation and different pollution factors. In addition, this article also expands the scope of application of the threshold model, enriching the quantitative analysis and research of epidemics and pollutants.

Author contribution Qiang Wang: Conceptualization, methodology, software, data curation, writing - original draft preparation, supervision, and writing - reviewing and editing. Xiaowei Wang: Methodology, software, investigation, writing - original draft, and writing - reviewing and editing.

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Data Availability The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate Not applicable

Consent for publication Not applicable

Competing interests The authors declare no competing interests.

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