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The Impact of the COVID-19 Pandemic on Major Air Quality Indicators in China and the United States

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Abstract: After the COVID-19 pandemic, some countries have restricted and blocked economic activities, which affects industrial production to a certain extent. This may lead to improved air quality. Different countries worldwide adopt different restrictions during the pandemic, which may also affect air quality at different levels. To verify the degree of environmental impact, the article selects the two representative economies in the world – China and the United States. These two countries choose policies with varying degrees of strictness, which may cause different impacts on production and air quality. This article uses regression methods to analyze the leading environmental and industrial production indicators before and after the pandemic and determine the impact of changes in industrial production during the epidemic on the air quality during the epidemic, according to the regression analysis, the quality of the environment has improved due to the control measures on economic activities. Moreover, after the main control measures have ended, economic activities and environmental quality have quickly returned to their original levels.

Keywords: environment, COVID-19, pandemic control, industrial added value

1. Introduction

The blockade during COVID-19 has caused various significant impacts. Especially when it comes to one of the most important methods of controlling the spread of the virus - lockdown, it leads to a significant reduction in socio-economic activities. Therefore, it is assumed that it will reduce industrial production and transportation commuting, possibly reducing air pollutant emissions. There are two nations with larger economies: China and the US. These two nations are China and the US. Throughout COVID-19, the blockade's intensity fluctuated. determine the exact impact of the COVID-19 embargo on changes to the air quality and determine if such effects are permanent or transient. The period of this article is from 2018 to 2022, and the lockdown policies of these two economies are different, which has high comparative significance. Not many articles explicitly study the effects of COVID-19 on air quality indicators in China and the US. This article will fill the gap in this field.

The COVID-19 pandemic has decreased transportation, industrial productivity, and the consumption of fossil fuels [1]. In addition to the potential side effects of this unprecedented blockade, environmental pollution in many countries has also significantly decreased [2]. Reduced socioeconomic activity has resulted in a drop in the demand for fossil fuels globally. Reduced air pollutant emissions, and cleaner air [3]. Some scholars use specific indicators like AQI to determine

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the influence on air quality. In one article, the author tests the AQI scores of 314 significant Chinese cities after closure. They found that different response modes in different cities exhibit different sensitivities to changes in air pollution [4]. It shows that different lockdown policies have different impacts on air pollution indicators. Some authors analyzed ground data from 162 monitoring stations in 12 cities throughout the world, it was found that although the pollution level had decreased in the places where the lockdown had been lifted, improvements were only transitory [5]. For economic activity and energy consumption, the recovery response is relatively complex and has spatial heterogeneity [6].

Therefore, it is worthwhile to evaluate whether there is quantitative evidence to support a positive relationship between the very policies to improve the air quality and fight enhance air quality while battling the COVID-19 virus. The subsequent parts of the the essay will address whether the COVID-19 epidemic and changes in air quality are related and arrive at policy recommendations for policymakers by focusing on comparing two countries, China and the US, as representatives of the global economies.

2. Methodology

For China, the paper selected monthly data from January 2019 to June 2023 using regression analysis. This article selected indicators with average good air quality days and PM2.5 as the dependent variables and the primary environmental indicators. An efficient instrument for correctly portraying The Air Quality Index (AQI) measures air quality. When the indicator is high, poor local air quality is indicated. On the other hand, if the index is low, the air quality is good and there are fewer air pollutants there [7]. PM2.5 refers to airborne particles having a dynamic diameter of 2.5 m or less, which can linger in the atmosphere for a very long time [8]. Human activities mainly generate PM2.5 and significantly impact human health [9]. The paper choose it as one of the leading environmental indicators. Average good air quality days mean the average Air Quality Index (AQI) days are below 100. The paper selects four industrial-added value, and steel plant equipment operating rate because these four indicators can reflect the operational level of the country's industrial industry, and they demonstrate primary sources of pollutants.

This paper directly substitutes AQI for ADQ in the context of the US. The air quality index (AQI) can accurately depict environmental pollution levels since it expresses air quality and pollution issues intuitively [10]. Because relative indicators are not counted in the US, this article does not use ADQ. The table 1 below lists various indicators.

Table 1: Variable descriptions.

Variable type	Variable name	Symbol	Unit
Explained variable	Average good air quality days (in china)	ADQ	%
	Particulate Matter,2.5	PM2.5	μg/m3
	Air quality index (in the USA)	AQI	μg/m3
Explanatory variable	Operating rate of steel equipment	OSE	%
	Operating rate of power plant equipment	OPE	%
	Operating rate of oil equipment	OOE	%
	Industrial added value	IAV	%

Establish the following data model:

$$\mathrm{ADQ_t} = \alpha_0 + \alpha_1 \mathrm{OSE_t} + +\alpha_2 \mathrm{OPE_t} + \alpha_3 \mathrm{OOE_t} + \alpha_4 \mathrm{IAV_t} + \varepsilon_t \quad (1)$$

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$$\mathrm{PM2.5_t} = \beta_0 + \beta_1 \mathrm{OSE_t} + \beta_2 \mathrm{OPE_t} + \beta_3 \mathrm{OOE_t} + \beta_4 \mathrm{IAV_t} + \delta_t \tag{2}$$

$$\mathrm{AQI_t} = \gamma_0 + \gamma_1 \mathrm{OSE_t} + \gamma_2 \mathrm{OPE_t} + \gamma_3 \mathrm{OOE_t} + \gamma_4 \mathrm{IAV_t} + \theta_t \tag{3}$$

where t represents the t month. This model tests the impact of different operating rates on environmental pollution at different times. Exploring the significant changes operating rates and industrial growth will bring to environmental pollution.

3. Results

The results of descriptive analysis are shown on table 2 below.

Table 2: Discriptive statistics.

	Variable	n	Mean	Standard Deviation	Max	Min
China	ADQ	53	85.081	6.736	93.7	61.6
	PM2.5	53	33.189	13.522	66	16
	OSE	53	61.978	12.099	78.94	37.05
	OOE	53	60.84	11.006	73.85	29.81
	OPE	53	39.813	8.246	57.84	24.7
	IAV	53	5.547	7.289	35.1	-12.5
US	AQI	58	40.251	4.787	51.93	29.83
	PM2.5	58	7.957	1.556	12.98	5.63
	OSE	58	75.932	6.437	84.23	52.92
	OOE	58	96.127	4.671	101.56	80.12
	OPE	58	77.037	2.842	82.95	71.76
	IAV	58	0.66	5.794	16.2	-17.3

For china, from descriptive analysis, it can be seen that the average ADQ is 85.081, PM2.5 is 33.189, indicating that it is relatively normal. OSE is 61.978, OOE is 60.84. IAV is 5.547. For the US, from descriptive analysis, it can be seen that the average AQI is 40.251, PM2.5 is 7.957, indicating that it is relatively normal. OSE is 75.932, OOE is 96.127, OPE is 77.037, and the average IAV is 0.66. The next page is correlation analysis. The results are shown in Table 3 below.
Correlation analysis mainly analyzes whether two variables are correlated. Generally speaking, when significant at 5% level, it indicates that the two variables are correlated.

For China, from Table 3 above, it can be found that there is a correlation between ADQ, OSE, and OOE. The coefficient with OSE is -0.615, which is a negative correlation, while the coefficient with OOE is a positive correlation, with a coefficient value of 0.826. There is a correlation between PM2.5 and OPE and OOE, with coefficients of -0.464 and -0.280, both of which are negative correlations.

For the US, from Table, the correlation between AQI and OSE, OOE, IAV, and OPE can be discovered, with a negative correlation between OSE and OOE and a positive correlation between OPE and IAV; the correlation between PM2.5 and OSE, OOE, OPE, and IAV can be found, but it is negative for OOE. The paper will further do regression analysis. The result is shown below on Table 4.

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Table 3: Correlation analysis.

China	OSE	OOE	OPE	IAV	ADQ	PM2.5
OSE	1					
OOE	0.717	1				
OPE	0.641	0.550	1			
IAV	0.176	0.307	0.149	1		
ADQ	-0.615	0.826	0.192	-0.062	1	
PM2.5	-0.203	-0.280	-0.464	0.364	0.071	1
US	OSE	OOE	OPE	IAV	AQI	PM2.5
OSE	1					
OOE	0.701	1				
OPE	0.237	0.330	1			
IAV	0.711	0.505	0.082	1		
AQI	-0.086	-0.171	0.087	0.121	1	
PM2.5	0.114	-0.144	0.001	0.064	0.537	1

Table 4: Regression analysis.

	CN ADQ	CN PM25	US AQI	US PM25
OSE	-0.288*	0.318	-0.165	0.106*
	(0.115)	(0.218)	(0.164)	(0.054)
OPE	0.168*	-0.663*	0.139	0.027
	(0.106)	(0.2)	(0.23)	(0.076)
OOE	0.406*	-0.396*	-0.296*	-0.153*
	(0.161)	(0.304)	(0.189*)	(0.062*)
IAV	-0.151	0.326	0.337*	-0.005
	(0.127)	(0.24)	(0.151*)	(0.05)
Adj R2	0.114	0.212	0.07	0.049
F	2.679	4.498	12.078	11.728
D-W	1.876	1.758	1.899	1.837
n	53	53	58	58

$^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

For China, with OSE, OPE, OOE and IAV as independent variables and ADQ as dependent variable, regression analysis was carried out, Adj R2 was 0.114. Therefore, the independent variable's interpretation of the dependent variable reached 11.4%. F-test can find that p-value is equal to 0.043, less than 0.05. Therefore, at least one independent variable has a significant impact on ADQ, and the D-W value is 1.876, near 2. Therefore, there is no autocorrelation problem, and the VIF is less than 5. Therefore, there is no collinearity problem. The coefficient is -0.288 from the viewpoint of OSE, and the p-value is 0.016, which is less than 0.05. OSE has a negative and significant effect on ADQ as a result; ODE's regression coefficient is 0.406, p-value equals to 0.015, less than 0.05. Therefore, the impact of ODE on ADQ is positive and significant.

With OSE, OPE, OOE and IAV as independent variables and PM2.5 as dependent variable, regression analysis was carried out, adjusted R2 was 0.212, so the independent variable's interpretation of the dependent variable reached 21.2%. F-test showed that p-value was equal to 0.004, less than 0.01, and at least one independent variable had a significant impact on PM2.5. D-W was close to 2, there was no autocorrelation problem, and the VIF was less than 5, so there was no multicollinearity problem. From the perspective of OPE, the regression coefficient is -0.663, p-value is less than 0.01. Therefore, the impact of OPE on PM2.5 is negative and significant, while the impact of OSE, OOE, and IAV on PM2.5 is not significant.

For the US, regression analysis of AQI is conducted with OSE, OOE, OPE and IAV as independent variables and AQI as dependent variable. First, adjusted R^2 is equal to 0.07, so the explanation of independent variables OSE, OOE, OPE and IAV for AQI has reached 7%. Second, F-test can find that p-value is equal to 0.000, less than 0.05. Therefore, at least one of OSE, OOE, OPE and IAV will have a significant impact on AQI. D-W is equal to 1.899, nearly 2, so there is no autocorrelation problem, and the VIF values are all less than 5. Therefore, there is no collinearity problem. Specifically, the p-values of OSE and OPE are greater than 0.05, so their impact on AQI is not significant at 5% level. Secondly, the regression coefficient of OOE is -0.296, significant at 5% level. Therefore, the impact of OOE on AQI is negative and significant, while the regression coefficient of IAV is 0.337, significant at 5% level. Therefore, the impact of IAV on AQI is positive and significant.

Regression analysis on PM2.5 was carried out with OSE, OOE, OPE and IAV as independent variables and PM2.5 as dependent variable. First, R^2 was equal to 0.049, so the explanation of independent variables OSE, OOE, OPE and IAV for PM2.5 reached 4.9%. Second, F-test found that p-value was equal to 0.000, less than 0.05. Therefore, at least one of OSE, OOE, OPE and IAV would have a significant impact on PM2.5. D-W is equal to 1.837 and close to 2, so there is no autocorrelation problem, and the VIF values are all less than 5. Therefore, there is no collinearity problem. Specifically, the p-values of OPE and IAV are greater than 0.05, so their impact on PM2.5 is not significant. Secondly, the regression coefficient of OSE is 0.106, significant at 5% level, so the impact of OSE on PM2.5 is positive and significant. The influence of OOE on PM2.5 is negative and significant since the regression coefficient of OOE is -0.153 and the p value is less than 0.05.

4. Discussion

It has been determined that the pandemic's effects on the US economy cannot be ignored. The mining industry, transportation and warehousing, art, entertainment, leisure, accommodation, and catering services have been greatly affected by the pandemic. These industries are also industries that emit more pollution. As a result of these impacts, capacity utilization has fallen to an all-time low, while air quality has also improved substantially.

It can be found that the operating rate of major factories in China has been widely affected by the pandemic. This has led to the suspension of production and operations of many companies, especially in the most severely affected areas. Service industries such as tourism, catering, retail and entertainment were hit hard while leaving some positive impacts, such as a reduction in carbon emissions and a dramatic improvement in air quality as well.

5. Conclusion

This article aims to study the impact of the epidemic on major environmental indicators by analyzing the impact of changes in the operating rate and industrial growth index of major heavy-polluting industries after the epidemic on air quality. This article finds that the lockdown and restriction policies of the epidemic have reduced the operating rate of major heavily polluting industries and lowered the industrial growth index, thereby affecting the leading air quality indicators. The air quality indicators have improved, and the two countries' environmental indicators during the epidemic have shown positive development. After the end of the lockdown measures, with the recovery of operating rates in major heavily polluting industries, the leading air quality indicators have rebounded.

A comparison between China and the United States found that the leading air quality indicators in the United States are better than those in China. During the epidemic, due to the adoption of different policies targeting the epidemic. China has adopted a longer and stronger lockdown policy. There has been no significant change in the operating rate of heavily polluting industrial factories in the United States, nor has any significant change in air quality indicators. However, there have been significant changes in the operating rate and air quality indicators of heavily polluting factories in China. In the future, the government should balance the relationship between the environment and industrial development while controlling the epidemic well, paying attention to its dual impact on the economy and environment.

On the one hand, the two countries' leading average environmental indicators are calculated monthly. Unable to obtain many samples, the analysis may have some bias. At the same time, two substantial economies, China and the United States, have varying degrees of impact on different regions within their economies. In the future, the different levels of impact of the pandemic should be presented in detail based on the different regions of the two countries.

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