The Impact of COVID-19 Containment Measures on Air Quality: Evidence From China

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ABSTRACT

The Chinese government has implemented a set of containment measures to control the spread of COVID-19 pandemic. The epidemic restrictions caused large reductions in human mobility and economic activities, which influenced the air quality conditions as well. This study investigates the short-term impact of pandemic restrictions on air quality based on the daily city-level air quality data of 31 provincial capitals and municipalities in mainland China. In the baseline estimation, a linear regression model with fixed effects is employed to capture the pollution improvement effects. The heterogeneity analysis is examined as an extension of the central argument. The results indicate that epidemic restrictions significantly improved the air quality in sample cities during the government response period. Besides, the magnitudes of pollution improvement are greater in cities with larger population size, higher regional GDP, and more industrial activities. The findings highlight the close relationship between human activities and air pollution conditions.

Keywords: COVID-19, Air quality, Containment measures, Level I emergency response.

1. INTRODUCTION

As a global health emergency event, the outbreak of COVID-19 has caused unexpected shocks to the economy and society. The governments of most countries in the world have implemented containment measures on business operations and people's mobility to control the spread of this epidemic. These comprehensive measures aiming to keep social distancing have also changed human behaviors, which lead to the change of air quality.

The reduction in economic activities caused by COVID-19 provides a unique opportunity for investigating the impact of human activity on air quality during unexpected events. This study estimates the short-term impact of pandemic restrictions on air quality change based on the panel data of 31 provincial capitals and municipalities in mainland China. The daily city-level air pollution data and matched meteorological condition data are explored in the empirical analysis.

To capture the whole picture of air quality change related to COVID-19, this study first adopted a linear regression model with fixed effects to capture the impact of containment measures on air quality. Then, the robustness of research findings was checked by accounting for the potential winter heating effect and epicenter spillover effect using limited samples. Finally, a heterogeneity analysis was carried out to explore the underlying channels of the influence mechanism.

This study contributes to the emerging literature on the multidimensional effects of COVID-19 in the view of its environmental aspect. The findings show that human activities indeed have a huge impact on air quality circumstances, and the magnitudes of air quality improvement vary with the economic structure and population of different cities.

2. DATA COLLECTION

2.1. Study Regions

The sample regions are 31 cities scattered around mainland China, including 27 provincial capitals and 4 municipalities. According to the latest data from the 2019 China City Statistical Yearbook, the population living in the sample cities accounts for 19.12% of the national population, and 33.17% of national gross

domestic product (current price) are concentrated in these regions.

2.2. Data Collection

2.2.1. Independent Variable: Air Quality

The station monitoring air quality data obtained from the Ministry of Ecology and Environment of China. The dataset includes daily city-level readings of the Air quality index (AQI), NO_2, $PM_{2.5}$, PM_{10}, CO, SO_2 and O_3 concentrations. Human activities are major sources of ambient air pollution. Emission from road traffic, industrial operation and residential using all contribute to the pollution.

2.2.2. Dependent Variable: Containment Measures

This study uses the announcement date of level I emergency response, which is promulgated by the provincial government, as the treatment date to the corresponding provincial capitals. The dates of this government action are collected from policy reports and news media. In the context of level I emergency response, the local government can deploy epidemic control measures such as restrict public gathering activities, shutdown the traffic channel to epidemic center.

2.2.3. Control Variable: Meteorological Condition

The concentration of air pollution is jointly influenced by the meteorological condition and emission level. Therefore, it is necessary to add weather factors as control variables. Meteorological data are collected by Web scraping from 2345Tianqi website, which provides historical city-level meteorological data. Based on previous research and data availability, this study includes daily city-level maximum and minimum temperatures, maximum wind speed, and record of snow or rain as controls, to eliminate the confounding factor of weather conditions to air quality change.

3. EMPIRICAL STRATEGY

3.1. Baseline Model

Most of the existing literature use lockdown policy as the treatment, but the corresponding dates are not always the same in different papers. Actually, the cities without a formal lockdown policy implemented other similar counter-virus measures [1], which affected people's daily life and industrial operation as well. This concern was also pointed out in the research of Liu et al. (2020)[2], they indicated that the unlocked cities may be affected by the locked cities due to the chain effects.

Therefore, this study uses the level I emergency response announcement as the treatment variable, which has a clear treated date. The baseline model of the log-linear specification is adopted as below:

$$ln(Air_{i,t}) = \alpha_0 + \beta Response_{i,t} + W_{i,t} + \eta_i + \mu_t + \varepsilon_{i,t} \qquad (1)$$

where i denotes the city and t denotes the date. The dependent variable $ln(Air_{i,t})$ is a measure of air quality in city i on date t, which equals the logarithms of daily air quality measures. The treatment dummy $Response_{i,t}$ denotes whether the level I emergency response is announced in city i on date t, which takes value 1 during the response period and 0 otherwise. $W_{i,t}$ is a vector of control variables, which denotes daily weather conditions for city i on date t. Both city fixed effects η_i and time fixed effects μ_t are included in the regression model. $\varepsilon_{i,t}$ is the random error term. The primary interest coefficient β measures the impact of COVID-19 restrictions on air quality.

3.2. Heterogeneity Analysis

This section investigates whether the effect of COVID-19 containment measures on air quality varies among different cities according to their socio-economic characteristics of the cities. The following grouped regression model is fitted to examine the heterogenous effects:

$$ln(Air_{i*,t}) = \alpha_0 + \beta Response_{i*,t} + W_{i*,t} + \eta_{i*} + \mu_t + \varepsilon_{i*,t}$$
where
$$i* = \{i_H, i_L\}, \ i_H \in I_H = \{Above \ median \ group\}, \ i_L \in I_L = \{Below \ median \ group\}$$
(2)

The city-level characteristics used for analysis are population, regional GDP, regional GDP per capita, and the industrial structure of the primary, secondary and tertiary industries. Besides, the sample cities are split into two groups for separate regression, denoted the High group (H) and the Low group (L) based on the median value of the examined factors. The time window and the description of other variables are the same as the baseline model.

4. EMPIRICAL RESULTS

4.1. Descriptive Statistics

The empirical analysis used comprehensive data at a day-by-city level from January 1st to June 30th in 2020. This study merged the meteorological data into the air quality dataset using city and date to identify the unique observations. In total, the final dataset consists of 5642 observations (n=31, T=182). To verify the percentage

change of air quality associated with the COVID-19 containment measures, this study uses the logarithm form of independent variables AQI, NO_2, SO_2, $PM_{2.5}$, PM_{10}, CO and O_3 in regression. The summary statistics of the main variables are shown in Table 1.

Table 1. Summary statistics

Variable	Obs.	Mean	Std. Dev.	Max	Min	P25	P75
AQI	5642	77.54	44.21	500	18	49	92
NO2	5642	31.86	16.30	119	3	20	40
SO2	5642	9.87	7.10	74	2	6	12
PM25	5642	40.49	38.43	906	3	19	46
PM10	5642	67.13	48.34	974	6	35	85
CO	5642	0.79	0.40	4.70	0.1	0.6	0.9
O3	5642	96.68	41.78	283	4	69	119
MaxTemp	5642	17.86	10.73	40	-17	10	27
MinTemp	5642	8.76	10.70	28	-29	2	17
Wind	5642	2.24	0.81	6	1	2	3
Sn_Ra	5642	0.17	0.36	1	0	0	0
Response	5642	0.24	0.43	1	0	0	0

4.2. Baseline Regression Results

In this section, the baseline model is estimated to capture the air quality changes associated with the announcement of level I emergency response in sample cities. AQI and the other six pollutants in turn serve as independent variables. Weather conditions are included to control for the meteorological confounders to air quality. City fixed effects and month fixed effects are included to account for the temporal and regional variations. Table 2 presents the regression results of the baseline models.

The independent variables from column (1) to column (7) are the logarithm of AQI, NO_2, SO_2, $PM_{2.5}$, PM_{10}, CO and O_3. The most primary explanatory variable *Response* is equal to 1 during the period of level I emergency response period and 0 otherwise. Except for O_3 and SO_2, the coefficients of AQI and other four pollutants are all significantly negative, which suggests that, in 31 provincial capitals and municipalities, the air quality during the COVID-19 restriction period has been improved compared with other sample periods. To be specific, the value of AQI and the concentration of NO_2, $PM_{2.5}$, PM_{10} and CO decrease by 10.6%, 37.6%, 9.2%, 15.4% and 9.9%, respectively. The estimations for AQI, NO_2, SO_2, PM_{10} and CO are statistically significant at 1% level, while the estimation of $PM_{2.5}$ is statistically significant at 5% level.

The coefficient of column (3), which SO_2 acts as the independent variable, is also a negative value but not statistically significant. Generally, the largest sources of SO_2 emissions are from fossil fuel combustion at power plants and other industrial facilities. It is worth noting that the livelihood fundamental industries such as coal-fired power plants and heating boilers, as well as certain heavy chemical industries that have some uninterruptible processes still continued operation during restriction time periods. This realistic context may lead to the weaker economic (lower reduction magnitude) and statistical significance (lower significant level) of SO_2 compared with other air quality measure indicators.

Table 2. The estimation results of baseline model

Variables	(1) ln (AQI)	(2) ln (NO_2)	(3) ln (SO_2)	(4) ln ($PM_{2.5}$)	(5) ln (PM_{10})	(6) ln (CO)	(7) ln (O_3)
Response	-0.106***	-0.376***	-0.040	-0.092**	-0.154***	-0.099***	0.224***
	(0.030)	(0.048)	(0.038)	(0.035)	(0.036)	(0.026)	(0.027)
MaxTemp	0.021***	0.024***	0.028***	0.010	0.033***	-0.001	0.050***
	(0.005)	(0.003)	(0.003)	(0.006)	(0.005)	(0.004)	(0.006)
MinTemp	-0.013*	-0.018***	-0.029***	-0.007	-0.019**	-0.000	-0.026***
	(0.007)	(0.004)	(0.006)	(0.010)	(0.009)	(0.004)	(0.008)
Wind	-0.112***	-0.279***	-0.136***	-0.218***	-0.095***	-0.163***	0.014
	(0.014)	(0.018)	(0.018)	(0.025)	(0.022)	(0.018)	(0.011)
Sn_Ra	-0.199***	0.012	-0.129***	-0.169***	-0.260***	0.012	-0.139***
	(0.022)	(0.020)	(0.015)	(0.032)	(0.027)	(0.018)	(0.027)
Constant	4.280***	3.760***	2.197***	3.848***	3.871***	0.078	3.743***
	(0.067)	(0.057)	(0.077)	(0.078)	(0.059)	(0.070)	(0.071)
City FE	YES	YES	YES	YES	YES	YES	YES
Moth FE	YES	YES	YES	YES	YES	YES	YES
Observations	5,642	5,642	5,642	5,642	5,642	5,642	5,642
R-squared	0.407	0.647	0.655	0.504	0.495	0.490	0.593

Notes: Standard errors are clustered at the city level and reported below the coefficients.

*** p<0.01, ** p<0.05, * p<0.1.

The coefficient of column (7) is significantly positive, which means that the concentration of O_3 during the government response period is much higher than the other sample time. It can be explained from the perspective of atmospheric chemistry that the level of precursor emissions was mainly responsible for the observed increase of O_3 [3]. In addition, the change direction between NO_2 and O_3 are generally opposite. The R-squared values of the baseline model are about 0.5 or a bit higher, which means that the adopted regression model is relatively fitted well with observations, and there are still some confounding factors that affect air quality.

4.3. Robustness Checks

To validate the robustness of baseline results, this study conducts two additional estimations using the limited panel sample. First, the time window is limited before the end date of winter heating. This analysis takes into account the possibility that air pollution decreased because of less emission from heating boilers after the winter seasons. The date 15th March 2020 is chosen to divide the whole period, that is, only uses the dataset before 15th March to fit the baseline model. Second, the epicenter Wuhan city is excluded from the original sample regions. The most severe lockdown implemented in Wuhan since January 23rd, during the lockdown period, human activities decreased to the lowest level. This analysis drops the observations in Wuhan to eliminate the potentially huge impact of the epicenter to reduce pollution spillover. The results are shown in Table 3.

Panel A of Table 3 shows the results of winter heating check. The coefficients are similar to the baseline models with a slightly changed significance level. This finding means that the end of heating season has a little influence on certain pollutants. Panel B of Table 3 presents the results of epicenter spillover check, the coefficients and significance are very similar to the earlier benchmark results. This indicates that the impact of epidemic restrictions on air quality is not driven by the most severely attacked area, all sample cities experienced a reduction in air pollution during the response period.

Table 3. The estimation results of robustness checks

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ln (AQI)	ln (NO_2)	ln (SO_2)	ln ($PM_{2.5}$)	ln (PM_{10})	ln (CO)	ln (O_3)
Panel A	*limited sample-before the end of winter heating date with same cities*						
Response$_A$	-0.061	-0.423***	-0.013	-0.020	-0.145***	-0.053*	0.328***
	(0.040)	(0.048)	(0.026)	(0.049)	(0.044)	(0.031)	(0.032)
Observations	2,325	2,325	2,325	2,325	2,325	2,325	2,325
R-squared	0.494	0.736	0.806	0.559	0.549	0.552	0.525
Panel B	*limited sample-drop the epicenter city Wuhan with same time window*						
Response$_B$	-0.112***	-0.380***	-0.061*	-0.103***	-0.161***	-0.112***	0.221***
	(0.031)	(0.051)	(0.034)	(0.036)	(0.038)	(0.025)	(0.030)
Observations	5,460	5,460	5,460	5,460	5,460	5,460	5,460
R-squared	0.406	0.651	0.661	0.507	0.497	0.496	0.591
Weather C.	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES
Moth FE	YES	YES	YES	YES	YES	YES	YES

Notes: Standard errors are clustered at the city level and reported below the coefficients.

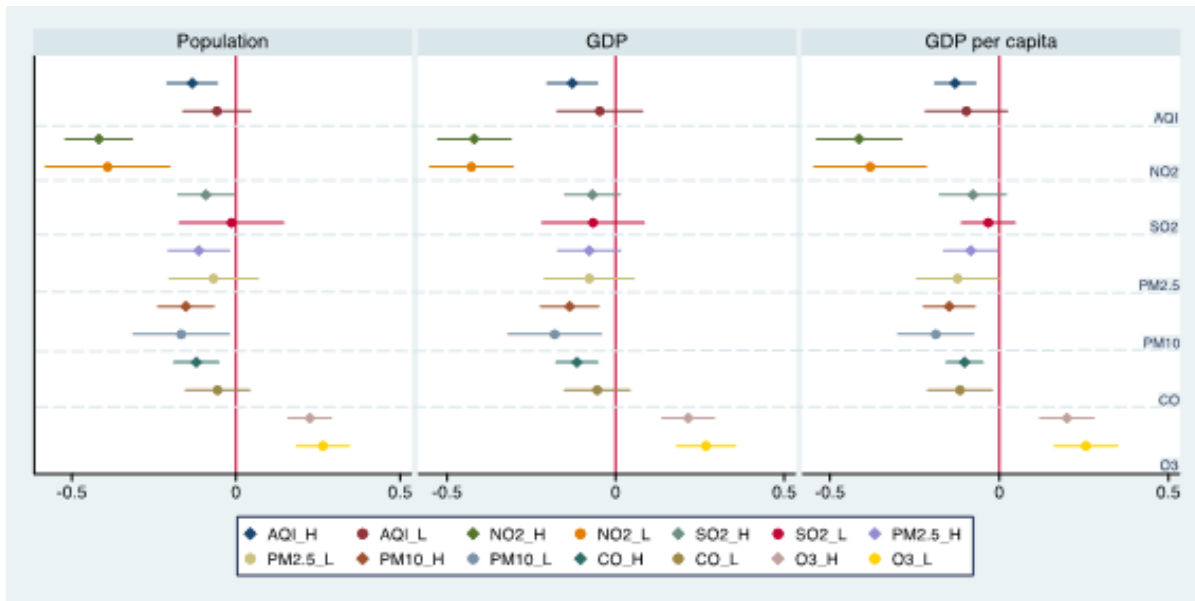*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Figure 1 Heterogeneity analysis associated with population, GDP and GDP per capita.
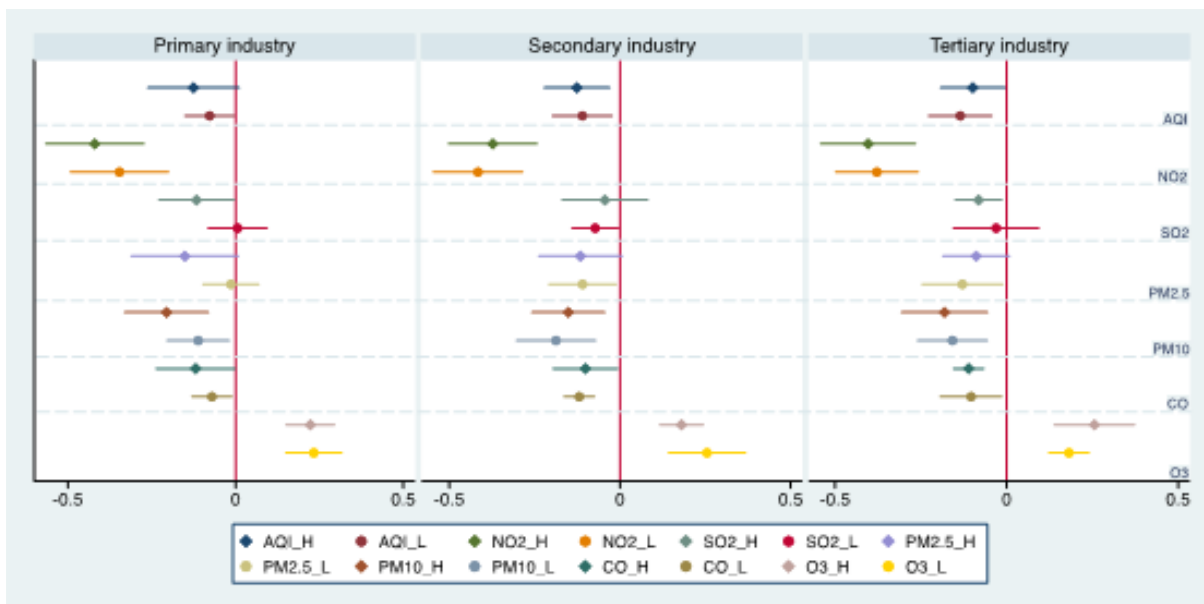

Figure 2 Heterogeneity analysis associated with industrial structures.

4.4. Heterogeneity Analysis

To test the heterogeneous effects of the air quality improvement in sample cities, this section examines the different reduction magnitudes according to city-level socio-economic characteristics. Figure 1 and Figure 2 plot the grouped regression results of AQI and the other six pollutants, including the coefficient pairs and corresponding confidence intervals. Each row means a separate regression using a subsample. The short horizontal lines are confidence intervals. The diamond symbol denotes the High group while the circle symbol demotes the Low group. In Figure 1, three subgraphs from left to right separately split sample cities according to their population, regional GDP and regional GDP per capita. In Figure 2, three subgraphs from left to right

divide sample cities according to their proportion of the primary industry, secondary industry, and tertiary industry in GDP.

Three subgraphs in Figure 1 show that the sample cities with larger population size, higher regional GDP and higher regional GDP per capita experienced a more considerable decrease in air pollution due to the COVID-19 restrictions. The explanation may be that agglomerated economies usually have a higher level of energy consumption, accompanied by more concentrated economic activities.

Three subgraphs in Figure 2 explore the heterogeneity of restriction impacts relevant to industrial structures in different cities. Based on the air quality indicator of AQI, these graphs show that the sample

regions with higher proportions of primary industry and secondary industry experienced a larger air pollution decrease during the government response period, the improvement effects are relatively low in the sample cities with more developed tertiary industry. In addition, different heterogeneity pattern also exists between different type of air pollutants.

5. CONCLUSION AND DISCUSSION

The COVID-19 pandemic has caused a far-reaching impact on the global economy and society. After the outbreak, business activity, transport traffic, and industry operation have largely decreased due to the counter-virus measures. This paper examines the air quality change related to epidemic restrictions in the Chinese context.

The research findings show that, in the short-term, the containment measures response to COVID-19 caused an unexpected improvement of air quality. Besides, the air quality improvement impact is greater in regions with large populations, developed economies, and high levels of industrial activity. The limitation is that this study only includes weather data in the linear specification, which ignores the possible non-linear relationship between weather and air quality.

Overall, this paper provides evidence of the unexpected air quality improvement associated with COVID-19 containment measures. The bulk of pollution reduction is attributed to decreased human travels and reduced industry operations relative to normal time. These findings highlight the close relationship between human activities and air pollution conditions.

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