Impacts of the COVID-19 Pandemic on Ambient Air Quality in China: Atox Quasi-difference-in-difference Approach

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2 **quasi-Difference-in-Difference Approach**

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The Impact of Lockdown on Urban Ambient Air Quality during the COVID-19 Pandemic in China: A quasi-Difference-in-Difference Approach

Abstract: The novel coronavirus pandemic (COVID-19) outbreak has provided a distinct opportunity to explore the mechanisms by which human activities affect air quality and pollution emissions. We conduct a quasi-difference-in-differences (DID) analysis of the impacts of lockdown measures on air pollution during the first wave of COVID-19 pandemic in China. Our study covers 367 cities from the beginning of the lockdown on January 23, 2020 until April 22, two weeks after the lockdown in epicenter was lifted. Static and dynamic analysis of the average treatment effects of treated effects is conducted for the air quality index (AQI) and six criteria pollutants. The results indicate that, first, on average, the AQI decreased by about 7%. However, it was still over the threshold of the World Health Organization (WHO). Second, we detect heterogeneous changes in the level of different pollutants, which suggests heterogeneous impacts of the lockdown on human activities: carbon monoxide (CO) had the biggest drop of about 30% and nitrogen dioxide (NO₂) had the second-biggest drop of 20%. In contrast, ozone (O₃) increased by 3.74% due to the improvement of visibility. We project that it would reduce the premature deaths related to air pollution by 150 thousand nationwide during the research period, which is much larger than the death due to COVID-19 infections. Third, air pollution rebounded immediately after the number of infections dropped, which indicates a swift recovery of human activities. This study provides insights for the implementation of environmental policies in China and other developing countries.

Keywords: COVID-19, Lockdown, Ambient Air Quality, Air Pollution Emissions, quasi-Difference-in-Difference

JEL codes: Q51, Q52, Q53

1. Introduction

At the end of 2019, an unusual coronavirus disease, eventually named COVID-19, was identified in Wuhan, China (Zhu et al., 2020). To curb its spread and ensure public health, the Chinese government enacted lockdown measures in the epicenter on January 23rd. The lockdown was expanded to the rest of the country soon after (Lau et al., 2020). Non-essential business were closed, and residents were quarantined home in order to cut off the viral transmission (He, G. et al., 2020). The drastic lockdown worked successfully (Ji et al., 2020; Sun et al., 2020), and it took 76 days for the epicenter to reopen.

These measures significantly reduced industrial, business, and residential activities (Muhammad et al., 2020). One of the most concerned aspect is that, energy consumption is reduced by the drastic lockdown measures and the cessation of human activities (Elavarasan et al., 2020). For instance, Wang, Q. et al. (2020) suggest that the fossil fuel related CO₂ emission in China decreased by 18.7% YOY in the first quarter. Since ambient air quality is found to be closely related with the energy consumption, prior studies find that the air quality is improved dramatically (Dutheil et al., 2020). He, C. et al. (2020) find that the operating vent numbers of NO_x decreased by 24.68% in China during the epidemic period, which would reduce the NO_x concentration by 9.54 ± 6.00 .

The pandemic provided a distinct opportunity to examine the mechanisms and ways in which human activities affect air quality and pollution emissions. Moreover, in-depth research through a quasi-experiment of nature is worth conducting (Verma and Gustafsson, 2020). However, previous research has some limitations. First, most of the recent findings are based on descriptive-comparative methods, and the lack of proper identification strategies threatens the validity of their results; for instance, the direct comparison of air quality before and after lockdown overestimates the impacts of the lockdown, as seasonal trends are ignored. Second, most previous studies only cover a short time span, which limits comprehensive interpretation not only on the shrinkage but also on the rebound effect (He, C. et al., 2020). The rebound effect is of more concern since it captures the recovery of economy from the deadly shock of COVID-19. Third, the results of previous research are most static and lack a dynamic analysis.

Therefore, we adopt a quasi-difference-in-difference (quasi-DID) approach, which enables the comparison of air quality between the epidemical period in 2020 and Chinese New Year's Leave in 2019, to estimate the net impact of the lockdown during the first peak of COVID-19. Moreover, through dynamic analysis, we identify the varying impact of the lockdown on air quality, which facilitate our understanding of human responses to the epidemic.

Our results suggest that, first, on average, the air quality index (AQI) decreased by about 7%. Although our results indicate immense improvements, the air quality was still over the threshold of the World Health Organization (WHO) and Chinese health

standards. Second, we detect significant heterogeneous impacts on different pollutants. Carbon monoxide (CO) had the highest biggest drop of about 30%, and nitrogen dioxide (NO₂) had the second highest drop of about 20%. In contrast, ozone (O₃) increased by 3.74% due to the improvement of visibility. Accordingly, it would reduce the premature deaths by 150 thousand nationwide. Third, although the AQI fell steeply after the lockdown, it increased immediately after the number of novel infections dropped, which indicates a swift economic recovery. In addition, we document preliminary cues of the rebound effect immediately after the lifting of lockdown measures in Wuhan.

This study's contribution to the literature is two-fold. First, compared with the recent studies in this field, our time span covers the whole epidemic period, from the launch of lockdown in January 23 to two weeks after the lift of lockdown in Wuhan. Therefore, it enables us to not only identify the shrinkage but also study the rebound of air pollution and human activities, which is more relevant to current unlocking process in most regions. To the best of our knowledge, this is the first study that identifies the dynamic impacts of lockdown measures on the environment. Second, this study also contributes to future environmental policy measures. Although temporary shutdown of pollution-intensive plants has become a common practice during periods of extreme air pollution, the impact of such emergency measures is still unclear. Our research sheds light on the mechanisms of human activities affecting air quality and pollution emissions.

The remainder of this paper is organized as follows. Section 2 provides information on the data sources and empirical methodology. Section 3 presents the average effect of the lockdown on the air quality in China. Section 4 reports the dynamic patterns of the effects of the COVID-19 lockdown. Finally, section 5 summarizes this study and discusses its limitations.

2. Data and empirical methodology

2.1. Datasets

In this study, we combine three datasets: hourly real-time reports of air pollutants, daily historical meteorological information, and pandemic data. All three datasets are at the prefecture level and county level and cover 367 cities in China.

Air quality data are collected from the China National Urban Air Quality Real-time Publishing Platform sponsored by the China National Environmental Monitoring Center. The platform reports the concentrations of six air pollutants—SO₂, NO₂, CO, O₃, PM₁₀, and PM_{2.5} (in micrograms (μg) per cubic meter under standard conditions)—as well as the aggregate AQI based on *the Chinese Technical Regulation on Ambient Air Quality Index*. Its wide coverage facilitates our investigation of the epidemical impacts of different human activities. For example, NO₂ is a good tracker of transportation in urban areas (He, M.Z. et al., 2020), while SO₂ is by and large the flue gas of coal-fired boilers (He, L. et al., 2020). Notably, air quality monitoring

stations are always located within urban areas, especially for prefecture-level cities(Hao and Xie, 2018). Therefore, the pollution data largely represent air quality in the downtown areas of cities.

We collect prefectural infection data from a public GitHub repository and crosscheck the data against official daily reports by the National Health and Family Planning Commission. This dataset contains daily cumulative confirmed cases, cumulative death toll, and cumulative recovered cases for each infected city since December 1, 2019, when the first case was traced back in Wuhan.

Meteorological conditions are also influential factors for ambient air quality (Chan and Kwok, 2001; He et al., 2017; Zhao et al., 2018). We derive daily meteorological information from the website of the China Meteorological Data Service Center. The data reported by meteorological stations located in the downtowns of cities are chosen so as to match our air quality information. Therefore, we could control the meteorological condition including temperature(Jayamurugan et al., 2013), precipitation(Tu et al., 2005), and wind(Chen et al., 2015), which affect the transmission of air pollutants.

2.2. *Quasi-DID identification*

2.2.1. *Identification strategy*

We build a quasi-DID model to identify the causal relationship. As illustrated in Fig. 1, if the influence of meteorological conditions is not considered, there is a clear reversal in air quality during the Chinese new year holiday (Tan et al., 2009; Feng et al., 2012). As the new year approaches, factories shut down and release their workers so that they can go home and meet their families during the spring festival (January 24 to January 30, 2020)(Tan et al., 2013). In addition, most industrial plants stay closed until the end of the holiday(Hua et al., 2020).

The lockdown measures induced by the COVID-19 pandemic have functioned similarly to the usual new year holiday period (Wilder-Smith and Freedman, 2020). Residents are required to stay at home and are only allowed to visit nearby grocery stores. Most factories are temporarily shut down(Sun et al., 2020). Therefore, non-essential industrial activities are restricted. Highways as well as major carriageways are completely blocked. Only vehicles with special permissions can travel across jurisdictions(Pepe et al., 2020).

Therefore, it is feasible to compare the air quality between the epidemical period in 2020 and the Chinese New Year's leave in 2019 to estimate the net impact of the COVID-19 lockdown. Day zero in 2019 is set as the dawn of Chinese New Year's leave, which is on February 5, while day zero in 2020 is set as the beginning of the lockdown period for most Hubei cities, which is January 23. We choose April 22 as the end of our research period, two weeks after Wuhan lifted its lockdown and resumed transportation conditionally on April 8.

As shown in Fig. 1, we can calculate the daily impact, which is given by the

concentration of air pollutants in 2019 minus that in 2020. We can also identify the dynamic impacts day by day. In addition, the dotted area, as the integral of impact over time, represents the aggregated impact of the COVID-19 lockdown on air quality. Compared to the single difference model in other studies such as Li et al. (2020), our DID approach can eliminate the impact of the new year holiday; hence, it is more accurate in estimating the average treatment effects of treated persons.

Our .

Fig. 1. Illustration of an identification strategy

Note: This figure illustrates the quasi-DID approach in this study. Day zero in 2019 is set as the dawn of Chinese New Year's leave, which is on February 5, while day zero in 2020 is set as the beginning of the lockdown period for most Hubei cities, which is January 23. We choose April 22 as the end of our research period in 2020, which is two weeks after Wuhan lifted its lockdown and resumed transportation conditionally on April 8.

2.2.2. The average effect on air pollution

Based on the above analysis, we evaluate the treatment impact of the COVID-19 epidemic on air pollution with the following DID regression equation:

$$y_{it} = \gamma Treat_i \times Post_t + \beta_1 Treat_i + \beta_2 Post_t + \Gamma X_{it} + \eta_i + \delta_t + \varepsilon_{it} \quad (1)$$

where the dependent variable y_{it} is the proxy for air quality. The dummy variable $Treat_i$ takes “1” for observations in 2020 and “0” for those in 2019. The dummy variable $Post_t$ takes “1” for periods after January 23 in 2020 and “1” for periods after February 5 in 2019. The term η_i captures the prefectural fixed effects, δ_t is the time fixed effects, ε_{it} is the random error term.

In addition, we control for a full set of daily meteorological variates X_{it} in

Equation (1) following previous research (Shi et al., 2016; Guo and Shi, 2017). X_{it} contains the highest and lowest temperature, the Cardinal directions, the Beaufort scale of predominant winds in 24 hours, and a dummy for rainy days.

The coefficient obtained by the first difference before and after the lockdown in 2020 is $\gamma + \beta_2$. Also, the coefficient obtained by the first difference before and after the Spring Festival in 2019 is β_2 . Differentiate the two difference results again, so γ captures the net effect of the lockdown measures after the outbreak of epidemic.

2.2.3. Dynamic impacts on air pollution

We investigate the dynamic evolution of the impacts on air pollution by using the following equation:

$$y_{it} = \sum_{t=1}^n \gamma_t Treat_i \times Post_t + \beta_1 Treat_i + \beta_2 Post_t + \Gamma X_{it} + \eta_i + \varepsilon_{it} \quad (2)$$

where $Post_t$ is the dummy variable for a specific period after day zero. In our analysis framework, $Post_t$ is defined as the t_{th} week after the launch of the lockdown. Therefore, the coefficient γ_t captures the net effects during its corresponding week t .

2.3. Summary statistics

We report the summary statistics of the urban ambient AQI for the two periods in Table 1. The observations in the control group and treatment group are divided into pre-periods before the event day and post periods after the event day.

Panel A reports the summary statistics for the control group in 2019. The average AQI for the whole period, pre-period, and post-period are 77.32, 92.40, and 71.55, respectively. Compared to the pre-period, the average AQI decreased by 20.85, or 22.56%. We find a similar pattern in the change in the median. The medians of the three periods are 64.21, 78.94, and 61.08, respectively. Moreover, we find a sharp decrease of 17.86, or 22.62% in the median of AQI. The decrease is likely to be attributed to two factors: the seasonal change caused by meteorological conditions and socio-economic factors such as the spring festival.

Panel B reports the summary statistics of the control group in 2020. The decrease recurs in that year. For example, the average AQI for the whole period, pre-period, and post-period are 67.86, 90.25, and 62.32, respectively. Compared with the pre-period, the average AQI decreased by 27.93, or 30.95%. The medians of the three periods are 56.58, 72.71, and 54.25, respectively. In addition, we find a sharp decrease of 18.45 or 25.37% in the median of AQI. The decrease is likely to be attributed to two factors: the seasonal change caused by meteorological conditions and socio-economic factors such as the lockdown measures induced by the COVID-19 pandemic.

As for the quasi-DID design, we could roughly estimate the impacts of the COVID-19 lockdown on AQI by subtracting the AQI decrease in 2020 from the decrease in 2019. For instance, the average treatment effect is roughly 7.07 for the AQI if meteorological conditions stay the same in both years. Although the decline is significant, the AQI is still above the healthy level recommended by the WHO, and outdoor air quality is still unhealthy according to environmental non-government organizations (World Health Organization, 2006).

Column (1) of Panel C reports the comparisons of the group mean and the results of the T-test for the AQI. We can see that in the single difference design, the AQI decreases significantly in both years. However, the gap grew by 7.07 in 2020, which is 33.90% less than in 2019.

We also report comparisons of all types of air pollutants to obtain an integrated overview of the impacts. Five out of the six pollutants significantly decreased after the event day, except for O₃. Fine atmospheric particulate matter such as PM_{2.5} and PM₁₀ experienced the greatest drop. The levels of primary pollutants such as SO₂, NO₂, and CO also declined, which is confirmed by the pollution monitoring satellites of the National Aeronautics and Space Administration and the European Space Agency. The increase of O₃ can mainly be attributed to the seasonal change of ultraviolet (UV) rays in solar radiation, which is a photo catalyst for the generation of O₃ particles. Panel C also shows that the primary air pollutant during the COVID-19 pandemic is PM_{2.5}, whose levels are nearly twice as high as the annual limits recommended by the WHO. Other pollutants, such as NO₂ and SO₂, are well below their healthy levels.

We also illustrate the time-varying patterns of the AQI and NO₂ for regions of varying epidemical severity in Fig. 2 and Fig. 3, respectively. To show the impact of the COVID-19 lockdown on air pollution, the whole sample is classified into four groups based on their epidemical severity in sequence, namely, Wuhan city, cities inside Hubei Province, cities outside Hubei Province, and the full sample. The pattern for the AQI and NO₂ are quite similar except that the changes in NO₂ levels are typical. In the epicenter, Wuhan, we see a steep drop immediately after the lockdown. The pollution level stayed at its background concentration rate for nearly twelve weeks. The background concentration rate is a tracker of fundamental human activities which are not affected by the lockdown measures, for example, the transportation of daily necessities. Moreover, after the lockdown was lifted, the concentration gradually increased and returned to its normal level, just as it was in 2019. The pattern of pollution experienced in the cities in Hubei Province is similar to that in Wuhan. However, for the average city in China, the concentration of pollutants bounced back to normal levels around seven weeks after the event day, which is much quicker than in the epicenter. Fig. 4 depicts the time-varying patterns of SO₂, which shows that SO₂ emissions instead increased when the lockdown was implemented. The trend of SO₂ emissions was the same as in the previous year, but it was slightly lower than in the same period during the previous year, after about three weeks from

the date of the implementation of the lockdown. With the resumption of work, SO₂ emissions are higher than in the same period in the previous year due to increased industrial production.

The parallel trend assumption is essential for the counterfactual setting in the DID approach (Wooldridge, 2010). All these figures show roughly similar trends of air quality change before the zero-event day, which validates the parallel trend assumption.

Table 1. Summary Statistics of the Urban Ambient AQI

Panel A:2019 Sample							
	(1) Obs.	(2) Mean	(3) p10	(4) p25	(5) p50	(6) p75	(7) p90
All	45718	77.32	36.33	47.58	64.21	89.63	134.85
pre: [-22,-1]	7944	92.40	41.46	55.75	78.94	113.88	158.82
post: [0,93]	33444	71.55	35.92	46.46	61.08	81.42	116.79
Panel B:2020 Sample							
	(1) Obs.	(2) Mean	(3) p10	(4) p25	(5) p50	(6) p75	(7) p90
All	41960	67.86	27.96	39.21	56.58	79.05	116.71
pre: [-22,-1]	7955	90.25	31.90	46.96	72.71	116.94	179.36
post: [0,93]	33644	62.32	27.38	37.92	54.25	73.46	99.28
Panel C: Mean difference of city-level air pollutants							
	(1) pre:2019	(2) post:2019	(3) post-pre:2019	(1) pre:2020	(2) post:2020	(3) post-pre:2020	
AQI	92.40	71.55	-20.85***	90.25	62.32	-27.92***	
Type:							
SO2	16.42	11.42	-5.00***	14.21	10.48	-3.73***	
NO2	36.36	26.56	-9.80***	37.24	22.21	-15.03***	
CO	1.15	0.80	-0.34***	1.15	0.74	-0.41***	
O3	75.31	103.77	28.46***	69.24	100.84	31.6***	
PM2.5	63.43	41.97	-21.45***	65.18	38.52	-26.66***	
PM10	99.53	76.79	-22.73***	86.60	66.58	-20.02***	

Note: The summary statistics are calculated for the daily AQI of all cities in the sample. The unit for air pollutants is µg per cubic meters under standard conditions. The day zero is January 23, 2020 (the date when the Wuhan lockdown was implemented), while the day zero for 2019 is February 5, 2019. The pre-period is defined as [-22, -1], while the post-period is defined as [0, 93], according to the event date 0. *** p<0.01, ** p<0.05, * p<0.1.

Fig. 2. The time-varying patterns of the AQI for different regions

Note: The daily average AQI is the average of the hourly AQI during the day. Our sample covers 367 prefecture-level and county-level cities in China. The sample period for 2019 is from January 14, 2019 to May 9, 2019, and the sample period for 2020 is from January 1, 2020 to April 22, 2020. The event date is defined as January 23, 2020 (the date when the Wuhan lockdown was enacted), while the event date of 2019 is defined as February 5, 2019, one day before the Chinese New Year's Eve. The red line displays the time series of the AQI of the sample period in 2020, while the blue line displays that for 2019. The spring festival for 2019 is manifested in dark grey and the lockdown period for 2020 is in light grey color.

Fig. 3. The time-varying patterns of NO₂ for different regions

Note: The daily average of NO₂ is the average of hourly NO₂ during the day. Others are the same as in Fig. 2.

Fig. 4. The time-varying patterns of SO₂ for different regions

Note: The average daily SO₂ is the average of hourly SO₂ during the day. Others are the same as in Fig. 2.

3. The average effect on air quality

We begin by estimating the average effect of the COVID-19 lockdown on the daily AQI, and we estimate the results of Equation (1) with the AQI as the dependent variable. Alternative sets of control variates are reported in Table 2. Column (1) reports a model with no control on meteorological variates. The average net impact of the COVID-19 lockdown on the AQI is -7.125. This result is similar to our estimates in Table 1.

Unfavorable weather conditions lead to an increase in the level of air pollutants, even when emissions remain unchanged (Mahmud et al., 2012; Wang et al., 2019). For example, high wind speeds lead to more dispersion of particulates (Megaritis et al., 2014). Furthermore, the effect of wind speed on air quality is continuous, and today's wind speed may affect air quality for several days. Therefore, in Column (2), we control the Beaufort scale of predominant winds in the current and in the past four days. In previous studies, only the wind on a particular day was analyzed (Shi et al., 2016; Guo and Shi, 2017). We find that the wind scale of a particular day has little impact because the diffusion of pollutants takes time. The lag terms are influential. Although the impacts of the wind scale fade away as time goes on, the wind will exert its impact even after four days. After we control for the wind condition, the effect declined to -5.604.

In addition to wind speed, temperature and humidity also have an impact on air quality. High temperatures can increase oxidation and production of sulfate but reduce nitrate levels through higher volatilization of particles to gas (Kota et al., 2018). In Columns (3) and (4), we control for the temperature and the rain dummy, respectively. In addition, in Column (5), we control for a full set of meteorological conditions. The ATT is smaller compared to Column (1), but it is still significant. The results indicate that the net impact of the COVID-19 lockdown on the AQI is -4.884, or -7.84% compared to what it was in 2019. Hence, our study suggests that news reports and former studies may exaggerate the impact of the COVID-19 lockdown on air pollution which fails to take into account the meteorological conditions. Our results support the findings of Wang, P. et al. (2020) that severe air pollution is associated with both anthropogenic activities and meteorological conditions.

Notably, the AQI reduction in our results is only half of that is estimated in He, G. et al. (2020). The major reason would be that they focused on the AQI in first month after the lockdown, by contrast, our study covers the full period of the lockdown from the beginning of the lockdown to two weeks after the reopen in Wuhan. Since their results are based on the first half of the lockdown period in which the most stringent quarantine measures are implemented, their results would overestimate the impacts on air pollution.

333 Ambient air pollution exposure has been found to correlate with respiratory(De
334 Leon et al., 2003; Ferkol and Schraufnagel, 2014) and cardiovascular(Franchini and
335 Mannucci, 2012; Lee et al., 2014) diseases, and leads to increased non-trauma
336 deaths(Schwartz, 2000; Landrigan, 2017). And pollution control measures will reduce
337 the premature deaths effectively even when implemented in a short period (Clancy et
338 al., 2002). It is reported that severe air pollution in China contributes to about 1.6
339 million premature deaths per year (Rohde and Muller, 2015). We project that the
340 decrease of air pollutants would reduce the premature deaths by 150 thousand
341 nationwide during the research period, according to the all-cause death rate estimated
342 by Dutheil et al. (2020). The number is dramatically much larger than the officially
343 reported death due to the COVID-19.

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Table 2. The Impact of the COVID-19 lockdown on ambient air quality

Dependent variable	AQI				
	(1)	(2)	(3)	(4)	(5)
Treat*Post	-7.125*** (1.605)	-5.604*** (1.842)	-4.749** (1.945)	-5.831*** (1.827)	-4.884** (1.944)
Treat	-1.412 (1.452)	-4.176*** (1.598)	-4.226*** (1.596)	-4.034** (1.588)	-4.172*** (1.602)
Wind Speed		-0.424 (0.296)	-0.559* (0.292)	-0.372 (0.296)	-0.478 (0.293)
L.Wind Speed		-6.094*** (0.461)	-6.033*** (0.462)	-6.088*** (0.460)	-6.072*** (0.459)
L2. Wind Speed		-5.146*** (0.311)	-5.172*** (0.309)	-5.151*** (0.311)	-5.163*** (0.307)
L3. Wind Speed		-2.759*** (0.286)	-2.799*** (0.280)	-2.763*** (0.286)	-2.865*** (0.283)
L4. Wind Speed		-2.037*** (0.314)	-2.199*** (0.294)	-2.054*** (0.314)	-2.219*** (0.293)
Temperature (Minimum)			0.093 (0.098)		0.120 (0.110)
Temperature (Highest)			0.385** (0.166)		0.396** (0.178)
sunny				1.189*** (0.433)	1.296*** (0.487)
Constant	100.713*** (1.937)	112.625*** (3.152)	112.971*** (3.078)	111.668*** (3.173)	117.206*** (4.102)
Date Dummy	Y	Y	Y	Y	Y
City Dummy	Y	Y	Y	Y	Y
Groups	367	335	335	335	335
Sample	83710	71597	71597	71597	71597
adj R2	0.127	0.141	0.143	0.141	0.144

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Note: This table reports the regression results of the average impact of the COVID-19 lockdown on the AQI of all cities in the sample. The dependent variable is the AQI of each city. The dummy variable treat is defined as 1 for observations in 2020, and 0 otherwise. Post is defined as 1 for the post periods [0,58], and otherwise 0. The event date 0 is defined as January 23, 2020 (the date on which the Wuhan lockdown was implemented), while the event date 0 for 2019 is defined as February 5, 2019. Standard errors reported in parentheses are clustered at the city level. *** p<0.01, ** p<0.05, * p<0.1.

The overall analysis confirms that the AQI level declined moderately due to the outbreak of COVID-19. However, one may wonder the level of which pollutant had the most drastic change. Table 3 reports the estimated results of each pollutant. Columns (1)-(6) report the results for SO₂, NO₂, CO, O₃, PM_{2.5}, and PM₁₀, respectively. The estimation results show diversified impacts of the lockdown measures on different air pollutants, which we elaborate as follows.

First, the average impact on SO₂ is positively significant at a 99.9 confidence interval. Surprisingly, the COVID-19 pandemic increased its concentration by 1.68 µg/m³, or 14.71% compared to 2019. It could be partly explained by the extension of the heating season in most northern cities. The statutory heating period ends at around March 15 every year. However, this year, residents have been required to stay in their houses due to the epidemic. Therefore, most local governments postponed the end of collective heating to mid-April. The extension of heating season in most northern cities and extended daily heating time increased SO₂ emissions due to the massive combustion of coal (Almond et al., 2009; Ebenstein et al., 2017).

Second, the concentration of NO₂ decreased by 5.11 µg/m³, or 19.24% compared to 2019. NO₂ is a good tracker of traffic intensity, especially in urban areas (He, L. et al., 2020; He, M.Z. et al., 2020). NO₂ has been identified as a typical pollutant, which is associated with lockdown measures around the world (Dutheil et al., 2020; Fattorini and Regoli, 2020; Mahato et al., 2020). Therefore, roughly speaking, on an average, we can estimate that VKT decreased by 20% during the period of three months after the lockdown.

Third, the concentration of CO decreased by 0.105 µg/m³, or 30.88% compared to 2019. Carbon monoxide is a by-product of the incomplete combustion of carbon-containing fuels, and on-road vehicles are the major source of CO in Chinese urban areas (Westerdahl et al., 2009; Ding et al., 2013). In addition, CO pollution mainly comes from small and medium passenger cars, while NO₂ emissions mainly comes from heavy-duty trucks in commercial vehicles. Therefore, as people remained sequestered in their residential areas, there were fewer passenger cars on the road than heavy-duty trucks, which led to a higher reduction of CO than NO₂.

Fourth, the concentration of ground-level O₃ increased by 3.881 µg/m³, or 3.74% compared to 2019. O₃ is formed when nitrogen oxides react with a group of volatile organic compounds (VOCs) under the ultraviolet rays in the presence of sunlight (Shao et al., 2009). The reduction of NO₂ changes the ratio of NO₂ to VOCs, resulting in an increase in O₃. Moreover, PM_{2.5} reduces atmospheric visibility and significantly blocks ultraviolet rays from sunshine, which further leads to an increase in O₃.

Finally, the concentration of PM_{2.5} decreased by 5.772 µg/m³, or 13.75% compared to 2019. As the most concerned pollutant, PM_{2.5} is a secondary pollutant, which is formed in the atmosphere through the reaction, coagulation, or nucleation of precursor gases, especially NO₂ and SO₂ (Hodan and Barnard, 2004). With the reduction of other pollutants, the level of PM_{2.5} declined.

396 **Table 3.** The Impact of the COVID-19 lockdown on different air pollutants

	(1)	(2)	(3)	(4)	(5)	(6)
	SO2	NO2	CO	O ₃	PM _{2.5}	PM ₁₀
	Concentration	Concentration	Concentration	Concentration	Concentration	Concentration
Treat*Post	1.679*** (0.343)	-5.113*** (0.402)	-0.105*** (0.012)	3.881*** (0.794)	-5.772*** (1.526)	2.721 (2.198)
Treat	-3.073*** (0.425)	-0.156 (0.427)	0.019 (0.013)	-3.134*** (0.605)	1.077 (1.347)	-11.821*** (1.647)
Wind Speed	-0.149** (0.067)	-0.120* (0.065)	-0.005** (0.002)	1.945*** (0.190)	-0.645*** (0.209)	0.725* (0.387)
L.Wind Speed	-1.391*** (0.106)	-4.008*** (0.113)	-0.075*** (0.004)	0.584*** (0.177)	-5.363*** (0.294)	-0.563 (0.645)
L2. Wind Speed	-1.239*** (0.094)	-3.363*** (0.105)	-0.084*** (0.004)	-2.013*** (0.183)	-7.452*** (0.346)	-6.733*** (0.476)
L3. Wind Speed	-0.458*** (0.056)	-0.879*** (0.069)	-0.038*** (0.003)	-2.036*** (0.173)	-3.954*** (0.295)	-4.282*** (0.428)
Temperature (Minimum)	0.129*** (0.020)	0.270*** (0.021)	-0.003*** (0.001)	2.105*** (0.076)	-0.242*** (0.087)	0.179 (0.139)
Temperature (Highest)	-0.241*** (0.027)	-0.362*** (0.031)	-0.002* (0.001)	-0.835*** (0.081)	0.314** (0.151)	0.649** (0.304)
No-rain	-0.322*** (0.076)	-0.735*** (0.101)	-0.029*** (0.003)	0.234 (0.329)	-0.735** (0.351)	0.711 (0.662)
Constant	22.881*** (1.059)	54.813*** (1.119)	1.648*** (0.040)	57.874*** (2.182)	108.913*** (3.177)	135.890*** (5.310)
Groups	335	335	335	335	335	335
Sample	72281	72281	72281	72281	72281	72281
adj R2	0.153	0.403	0.347	0.418	0.208	0.059

397 Note: This table reports the regression results of the average impact of the COVID-19 lockdown on each pollutant
398 for all cities in the sample. Standard errors reported in parentheses are clustered at the city level. *** p<0.01, **
399 p<0.05, * p<0.1.

400 **4. Discussion: The dynamic patterns of the lockdown effects**

401 To study the dynamic pattern of the air quality response to COVID-19, we estimated
402 Equation (2), with 13 dummy variables, *post0*, *post1*, ..., *post12*, interacting with the *treat*
403 dummy variable. The dummy variable *post0* is taken for the sample period [0, 6] after the
404 event date, while *post1*, ..., *post12* are taken for the subsequent twelve weeks.

405 Fig. 5 presents the path of the change in AQI. We also illustrate the change in the
406 number of new infections (in its logarithmic form) in the second axis to detect its impact.
407 In our quasi-DID design, the AQI decrease in Fig. 5 is the net impact, which is the level

in 2020, minus that in 2019. Therefore, we observe patterns similar to the mechanism in Fig. 1. In the first two weeks, the AQI level is quite the same as it was in 2019, which confirms our assumption that the effects of the lockdown measures and the New Year's holiday are comparable. In the third and fourth weeks, as the lockdown went on in most cities, the AQI level dropped by 20 points compared to 2019.

After week 4, the AQI climbed steeply to its normal level in three weeks. As the number of daily new infections dropped in early March, most cities gradually moved closer to normality; hence the treatment effect fades away. On average, the AQI steadily bounced back to its normal level about seven weeks after the end of the lockdown of Wuhan city. The temporary improvements owing to the lockdown only lasted for one month for the average city in mainland China.

The turning point comes just one month after the event day. Although most analysts thought that local governors were reluctant to reopen cities due to the fear of the epidemic bouncing back, our analysis shows that the AQI increased immediately after the novel infections dropped, which is a quick response. The AQI plateaued in four consecutive weeks after week 7. During this month, the AQI gradually returned to the same level that it was in the same period, previous year with the resumption of work. Finally, the AQI increased sharply in the last two weeks. We find strong rebound effects after April 8 in the last two weeks, immediately after the epicenter lifted its lockdown measures. It suggests that pollution-related industrial and business activities bounced back after 2019 as the government called for a restart of the economy.

Fig. 6 depicts the response of the AQI to daily new infections. The straight line in the scatterplot shows that greater the number of new infections each day, the better the air quality. When the number of daily new infections is greater, human activities are strictly monitored, and people are required to stay at home. As the number of daily new infections gradually decreases, control measures also gradually relax. At the same time, people start to resume work, and companies begin production activities, leading to a decline in air quality.

To sum up, our estimation suggests that the impact of the epidemic persisted for nearly four weeks, from January 23 to late February. Then it returned to its normal level and seesawed up and down for more than one month. Lastly, as the daily new infections went down and mass quarantine measures were relaxed and then eventually removed, and air pollution increased significantly.

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Fig. 5. The Dynamic AQI Response

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Note: This figure illustrates the dynamic air quality response. Changes in the daily AQI are the regression coefficients estimated from the DID regression on twelve dummy variables, $post_0, post_1, \dots, post_{11}$, interacting with a treat dummy variable. The dummy variable $post_0$ is taken for the sample period (0, 7) after the event date, while $post_1, \dots, post_{11}$ are taken for the subsequent seven weeks after the event date. Treat is equal to 1 for observations in 2020, and 0 for observations in 2019. The event date is defined as January 23, 2020 (the date when the Wuhan lockdown was implemented), while the event date for 2019 is taken to be February 5, 2019, one day before the 2019 Chinese New Year's Eve. The error bar in red indicates a 95% confidence interval. The incremental # of weekly novel COVID-19 cases is the total number of COVID-19 cases confirmed during the event week.

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Fig. 6. The response of the AQI to daily new infections

Note: this figure shows the impact of the daily new COVID-19 cases on the AQI across cities. Panel A displays the simple scatterplot between the AQI and the total number of COVID-19 cases as of April 22, 2020. We also included the fitted line in the scatterplot.

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458 Fig. 7 shows the dynamic concentration change of each major air pollutant. Although
459 their u-shape patterns are similar to that of the AQI, we find subtle differences for
460 pollutants, which are worth exploring. However, SO_2 exhibits a unique pattern during the
461 epidemic period. This is because most northern cities expanded their heating season from
462 mid-March to mid-April, which worsened SO_2 emissions.

463 Among the six pollutant criteria, the changes of NO_2 levels are the most typical. In the
464 urban areas, the major source of NO_2 emission is vehicles. Therefore, NO_2 concentration
465 is a good tracker of traffic. As is shown, in the first week, NO_2 has a similar intensity as in
466 2019. However, soon after, there is a steep decline in NO_2 levels, which suggests that
467 residents were still sequestered in their houses. It only started to increase after week 4.

468 The changing trend of $\text{PM}_{2.5}$ is like that of NO_2 . In the first two weeks, the level of
469 $\text{PM}_{2.5}$ was higher than that of the same period in the previous year, and then it plummeted.
470 It started to bounce back after the fourth week. However, it was always lower than the
471 $\text{PM}_{2.5}$ levels of the same period in 2019. In the eleventh week, it returns to a level higher

than that in 2019. The overall changing trend of PM_{10} also declined first and then increased. In the first week, the PM_{10} level was lower than that of the same period in the previous year, while in the second week it rose to the same level as that of the previous year, and then it began to decline. It started to bounce back after the fourth week. However, there was a decline from the fifth to the sixth week. Again, it continued to rise, and after eight weeks, it reached a level that was higher than that of the same period in the previous year. The main sources of $PM_{2.5}$ are the residues of power generation, industrial production, vehicle exhaust emissions, and coal burning (Sharma et al., 2020). Although power generation did not decrease, and coal burning increased, vehicle exhaust emissions and industrial production had greatly reduced, thus resulting in a reduction of $PM_{2.5}$ during the COVID-19 pandemic. However, most of the time, the PM_{10} level was higher than or equal to that of the same period in the previous year. It is most likely due to increased coal burning during the COVID-19 pandemic. Meanwhile, the reduction of certain pollutants in the atmosphere changes the composition ratio of substances, allowing compounds to interact to form more fine particles (Muhammad et al., 2020).

The O_3 level rose from the first week to the second week and then plummeted. However, it was not until the sixth week that for the first time, its level fell below that of the same period in the previous year. It then started to bounce back, and it was always higher than that of the same period in the previous year. The increase of O_3 can be explained by two reasons. First, the decrease in $PM_{2.5}$ and NO_x lead to the change in their ratios to VOCs, which in turn leads to the increase of O_3 concentration (Jiménez and Baldasano, 2004). The decrease of $PM_{2.5}$ concentrations reduced the scattering and absorption of sunlight, increased UV radiation, and led to a higher O_3 concentration (Wang et al., 2019). Second, the reduction of NO_x reduces the titration of O_3 in urban areas, and thus leads to higher O_3 concentrations (Mahato et al., 2020).

To sum up, the heterogeneous dynamic patterns of different pollutants are reflected in substantive human activities. Significant rebound effects are detected for almost all pollutants after the lockdown was lifted, which triggers our worry about the long-term impacts of the COVID-19 lockdown on air pollutions.

Fig. 7. Concentration Changes of Air Pollutants over Time: By Categories

Note: This figure presents the dynamic pollutant concentration responses by categories. Changes in daily average concentration are the regression coefficients estimated from the DID regression on 12 dummy variables, $post_0$, $post_1$, ..., $post_{11}$, interacting with a treat dummy variable. The dummy variable $post_0$ is defined for the sample period (0, 7] after the event date, while $post_1$, ..., $post_{11}$ are defined for the subsequent eleven weeks after the event date. Treat is equal to 1 for observations in 2020, and 0 for observations in 2019. The event date is taken as January. 23rd, 2020 (the date when the Wuhan lockdown was implemented), while the event date for 2019 is taken as Feb. 5, 2019, one day before the 2019 Chinese New Year's Eve. The error bar in red indicates a 95% confidence interval.

Although the above results indicate a quick rebound on average, there is a drastic heterogeneity. In Fig.8 we illustrate the heat map of the urban NO₂ concentration nationwide, which shows the spatial-temporal fluctuation of NO₂ concentration. In the Panel A, the NO₂ concentration three weeks before the lockdown could be taken as the business as usual (BSU) pattern. Three pollution hotspots are shown clearly including the Capital Region, the Yangtze River Delta, the Pearl River Delta, and the Sichuan Basin. Compared with Panel A, Panel B indicates that the lockdown reduced the NO₂ concentrations drastically and uniformly in the first week to the fourth week nationwide, as However, as shown in Panel E, air pollution rebounded much faster in the Yangtze River Delta and the Pearl River Delta, on the contrary, it restored much slower in other hotspots e.g., the Sichuan Basin and the Capital Region. The drastic heterogeneity in rebound may suggest the regional differences in industrial structures and other institutional factors. For example, the export sectors in the southern regions are more vital, especially the sector manufacturing the personal protective equipment (PPE), which is driven by the surge of infections in other countries.

Fig.8. Heat maps of weekly NO₂ concentration across China during the COVID-19 period

Notes: This figure presents the weekly average NO₂ concentration across China before and after the breakout of the epidemic. The epicenter, Hubei Province are marked by a red circle. The weekly average is adopted to curb the stochastic influence of weather conditions.

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525 **5. Conclusion**

526 In this study, we conduct a quasi-DID analysis of the impacts of lockdown measures on
527 air quality during the period of the epidemic in China. Our study covers 367
528 prefectural-level and county-level cities during the epidemic period from the beginning of
529 the lockdown until two weeks after the lifting of the lockdown in Wuhan. The results
530 suggest the following.

531 First, on average, the AQI decreased by about 7%. Although our results indicate immense
532 improvements, air quality levels were still over the threshold set by the WHO and by the
533 Chinese standards. Second, we detect significant heterogeneous impacts on different
534 pollutants. CO had the biggest drop of about 30%, and NO₂ had the second-largest drop of
535 about 20%. In contrast, O₃ increased by 3.74%. Third, although the AQI reduced steeply
536 after the lockdown, it increased immediately after the number of novel infections dropped,
537 which is a quick response. Finally, we also detect preliminary cues of the rebound effect,
538 immediately after the lifting of lockdown measures in Wuhan.

539 One limitation of our study is that as the epidemic is fading away, its long-term impacts
540 are still not clear. On the one hand, some suggest that there will be a degradation of the
541 environment due to the harsh and massive economic stimulus. On the other hand, the
542 COVID-19 pandemic is more infectious compared to the severe acute respiratory syndrome
543 (SARS) that emerged in 2002 in China. Lifestyles may change permanently. For example,
544 virtual meetings are held more frequently, and white-collar workers prefer working from
545 home. Moreover, instead of simply turning to the old playbook of investment stimulus, the
546 government has launched a new infrastructure initiative, which mainly incorporates
547 fifth-generation networks, industrial internet, inter-city transit systems, vehicle charging
548 stations, data centers, and several other projects. These policies would lead to more
549 sustainable growth. Therefore, in the future, we will need to expand the time window of the
550 lockdown to explore the effects of the COVID-19 lockdown and its medium and permanent
551 environmental effects.

552

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558 **Author Contribution:**

559 **Tuo Zhang:** Conceptualization, methodology, data collection, visualization, and writing the original draft
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562 **Conflict of Interest:**

The authors declare no conflict of interest in relation to the publication of this study.

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708

Figures

Figure 1

Illustration of an identification strategy

Figure 2

The time-varying patterns of the AQI for different regions

Figure 3

The time-varying patterns of NO₂ for different regions Note: The daily average of NO₂ is the average of hourly NO₂ during the day. Others are the same as in Fig. 2.

Figure 4

The time-varying patterns of SO₂ for different regions Note: The average daily SO₂ is the average of hourly SO₂ during the day. Others are the same as in Fig. 2.

Figure 5

The Dynamic AQI Response

Figure 6

The response of the AQI to daily new infections Note: this figure shows the impact of the daily new COVID-19 cases on the AQI across cities. Panel A displays the simple scatterplot between the AQI and the total number of COVID-19 cases as of April 22, 2020. We also included the fitted line in the scatterplot.

Figure 7

Concentration Changes of Air Pollutants over Time: By Categories Note: This figure presents the dynamic pollutant concentration responses by categories. Changes in daily average concentration are the regression coefficients estimated from the DID regression on 12 dummy variables, post0, post1, ..., post11, interacting with a treat dummy variable. The dummy variable post0 is defined for the sample period (0, 7] after the event date, while post1, ..., post11 are defined for the subsequent eleven weeks after the event date. Treat is equal to 1 for observations in 2020, and 0 for observations in 2019. The event date is taken as January. 23rd, 2020 (the date when the Wuhan lockdown was implemented), while the event date for 2019 is taken as Feb. 5, 2019, one day before the 2019 Chinese New Year's Eve. The error bar in red indicates a 95% confidence interval.

Figure 8

Heat maps of weekly NO₂ concentration across China during the COVID-19 period Notes: This figure presents the weekly average NO₂ concentration across China before and after the breakout of the epidemic. The epicenter, Hubei Province are marked by a red circle. The weekly average is adopted to curb the stochastic influence of weather conditions. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.