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The impact of the COVID-19 outbreak on the air quality in China: Evidence from a quasi-natural experiment



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ABSTRACT

The outbreak of coronavirus (COVID-19) in early 2020 posed a significant threat to people's health and economic sustainability in China and worldwide. This study investigated whether the lockdown measures precipitated by the COVID-19 pandemic affected air pollutants in the short term. Moreover, we investigated the impact of the heterogeneity of cities and regions. Using city-level daily panel data for the 2018–2020 lunar calendar, we employed a two-way fixed effects model and interrupted time-series analysis to inspect the effects of the lockdown measures. Interesting empirical findings emerged from our analysis. First, compared with the base period from 2018 to 2019, the COVID-19 lockdown measures significantly reduced air pollutants. In 2020, compared to 2018, PM₁₀ and SO₂ dropped by 15.28 μg/m³ and 6.55 μg/m³, and compared to 2019, PM_{2.5}, PM₁₀, and SO₂ declined by 7.4 μg/m³, 19.34 μg/m³, and 1.41 μg/m³, respectively. Second, our dynamic analysis showed that as more time elapsed since the start of the lockdown, the associated reduction in air pollution became more significant. Third, the proportion of secondary industries and the cumulative number of confirmed cases had a considerable heterogeneity impact on lockdown measures. Policymakers should encourage investment in new infrastructure and initiatives to boost efficiency and enhance environmental outcomes.

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1. Introduction

In recent years, environmental pollution, and particularly air pollution, has garnered increasing attention globally, especially in developing nations such as China. Since the economic reforms and the opening of China, the economy has entered a stage of rapid and extensive development. Simultaneously, the level of air pollution in China poses a significant health risk, including extensive premature mortality (Dong et al., 2018; He et al., 2016; Wang et al., 2016) where air pollution induces nearly a million people mortality per year (Yue et al., 2020). Air pollutants are primarily solid particles, including fine particulate matter (PM_{2.5}), inhalable particulate matter (PM₁₀), and sulfur dioxide (SO₂), that result from natural and human activities (Galindo et al., 2011; Miao et al., 2019). To control severe air pollution in China, the Chinese government implemented the Air Pollution Prevention and Control Action Plan from

2013 to 2017 (The State Council, 2013), which aimed to lower the concentrations of PM_{2.5} in cities by 10%–25% (Feng and Liao, 2016; Feng et al., 2019; Zhang et al., 2016). Additionally, the new Three-year Action Plan to win the Blue Sky Defense War (The State Council, 2018) from 2018 to 2020 aimed at lowering PM_{2.5} concentrations by 18% from the 2015 baseline. More specifically, and in addition to policies that can directly remedy external factors affecting air quality, the occurrence of certain major events may also impact air quality. In China, air quality have been controlled during large-scale events, competitions, and conferences, with noteworthy results, and is commonly referred to as the APEC Blue or Military Review Blue (Li et al., 2017) whereby the government often implemented short-term temporary control policies around a venue and provided samples that researchers analyze to determine the effect these major events have on air quality. A further consequence of air pollution includes reduced economic growth through damage to people's health—such as respiratory and heart complications—which in turn influences labor mobility and efficiency (Peretto and Valente, 2015).

Atmospheric processes that determine concentrations of air pollutants are nonlinear, and fluctuating weather plays a significant

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role in pollution formation, emphasizing the importance of meteorological and joint controls of pollutants (Li et al., 2019; Wang et al., 2019). Meteorological conditions and pollutant emission restrictions work together to influence air quality. Previous literature has revealed the impact of pollution controls, such as traffic and industrial emission controls, on air quality (Wang et al., 2014; Yu et al., 2019; Zhang et al., 2016). However, studies on the impact of policies that do not target pollution control on air quality are lacking.

In response to the coronavirus (COVID-19) outbreak, the central government in China implemented severe nationwide lockdown measures from the end of January 2020. Due to the restrictions and the Spring Festival (Kong et al., 2015), many factories ceased doing business, the traffic volume on roads declined, and the burning of fireworks was banned, especially in China's megacities. This provided an excellent opportunity to analyze the impact of such a long-term and continuous reduction of pollutant emissions on air quality. China had experienced several social disruptions, such as the Olympic Games, G20, and the Shanghai World Expo. Regardless of whether they were spontaneous or obligated, these activities tended to weaken production activities, but also provided unique opportunities for atmospheric research (Chan et al., 2015, 2019). One notable difference between the COVID-19 lockdown measures and previous social disruptions was that the latter has been more enduring. The COVID-19 pandemic broke out in Wuhan at the end of 2019 and was confirmed to involve human-to-human transmission in January 2020, resulting in Wuhan's isolation from other regions from January 23. Other provinces and cities subsequently adopted corresponding lockdown measures. As the epidemic came under control, the main cities in China gradually lifted lockdown measures from February 10. Of the disruptions to Chinese society in the past 50 years, the lockdown measures caused by COVID-19 had been the most protracted, and its impact on human society and economic activities was also the most severe. In this study, both Spring Festival and Lantern Festival were included in the study period, during Spring Festival people travel intensively (Lai and Pan, 2020; Li et al., 2016). The COVID-19 lockdown measures affected the return of labor from rural areas to cities after the Lantern Festival. In 2020, many migrant workers remained in their hometowns in the countryside after the Lantern Festival, unlike in previous years, when the number of migrant workers returning to their city would reach a peak after the Lantern Festival. This provided a natural control group for this study to identify the effects on air quality.

The single-difference method, the difference-in-difference method (DID) (Chen et al., 2013), regression discontinuity designs (RDD) (Hausman and Rapson, 2018; Neidell, 2010), and interrupted time-series analysis (Linden, 2015), among others, are frequently used in economics and social science to study the impact of environmental and air quality policies. Each technique has its advantages and weaknesses. When the government implements policies, there are factors such as expectations and pro-environmental enthusiasm, which could also affect policy implementation and air pollutants (Athey and Imbens, 2017), making the parallel trend hypothesis difficult to satisfy (Pei et al., 2020). Endogeneity problems cannot be effectively solved, which has become a considerable challenge in evaluating the impact of policies on air quality. The COVID-19 lockdown measures during the Chinese Spring Festival severely restricted social and economic activities nationally. Because the primary method of slowing the infection and death rates in China was to impose strict social distancing regulations, endogenous issues did not have a severe impact; thus, we used this exogenous shock to quantify the changes in air quality in megacities. The main aim of this study was to investigate how air pollutants were affected by lockdown measures in response to the

COVID-19 pandemic and to gain insights by comparing 2020 with 2019 and 2018 using the same lunar calendar. We also analyzed the heterogeneity of air quality changes arising from different urban characteristics during the period up to the Lantern Festival. The results confirmed an improvement in air quality which varied due to differences in urban industrial development and the prevalence of the COVID-19. Development suggestions for improving air quality were presented; possible future changes in living and office styles and the speeding up of the transformation of the industrial structure were also recommended. Finally, we discussed opportunities for saving energy and reducing emissions concerning new infrastructure, 5G, and other novel lifestyle changes.

Compared to the existing literature on the association between COVID-19 lockdown and air quality in China, our research made two important contributions. First, the coverage of this research was wider, including 31 megacities in China, whereas the existing literature only focuses on Wuhan or a few cities such as Beijing, Wuhan, and Guangzhou (Lian et al., 2020; Pei et al., 2020). Second, we used the lunar calendar for the control group and not the Gregorian calendar. Considering the Chinese Spring Festival Season and its associated travel rush, using the lunar calendar as a control group can reduce the effects of the Spring Festival in obtaining more reliable estimation results.

The novelties of this study are as follows:

a. From 10 days before the Spring Festival to 14 days after the Lantern Festival of the same lunar calendar, the equivalent national average daily coal consumption in 2020 decreased by 20.77% (2018) and 14.72% (2019). The average daily congestion index of China's five main cities—Shanghai, Chengdu, Guangzhou, Suzhou, and Zhengzhou—was 1.52 (2018), 1.43 (2017), and 1.19 (2020). Thus in 2020, when compared to the same period, this decreased by 22.22% (2018) and 15.6% (2019). The average daily subway ridership of all five cities was 3.93 million (2018), 4.192 million (2019), and 1.488 million (2020)—a comparative decreased in 2020 of 62.12% (2018) and 64.55% (2019), respectively.

b. During the same lunar calendar, after controlling for meteorological factors such as daytime and nighttime wind and temperature, dummy variables for rainfall, city, and year fixed effects, the estimation results showed that the improvements in air quality were both quantitatively and statistically significant. For 2020, PM₁₀ and SO₂ decreased by 15.28 μg/m³ and 6.55 μg/m³, respectively, from 2018, and compared to 2019, PM_{2.5} dropped by 7.4 μg/m³, PM₁₀ dropped by 19.34 μg/m³, and SO₂ dropped by 1.41 μg/m³.

c. In the analysis of heterogeneity, we found that for cities with a high proportion of secondary industries, the improvement in air quality in 2020 was more significant. Cities faced more severe infection rates (with more people diagnosed in COVID-19) had more significant air quality improvements.

2. Research design

COVID-19 epidemic suddenly struck Wuhan at the end of 2019 and soon spread to the rest of the world in 2020 (Zhu et al., 2020). To alleviate this epidemic, the Chinese government had adopted unprecedented strict measures throughout the country, such as social distancing and postponing the resumption of work and production. Thirty-one provinces and cities (except Hong Kong, Macao, and Taiwan) initiated the first-level response to major public health emergencies. The number of confirmed cases in China reached an inflection point around the time of the Lantern Festival. The timing of the outbreak corresponded to leisure travel during the Spring Festival and resumption of labor after the Lantern Festival (Fig. A in appendix). This provided a precious sample for examining how air quality responds to rapidly declining anthropogenic emissions on a national scale, which provided a critical

foundation for our understanding and development of relevant policies. The overall research thinking of this study was described by Fig. 1.

2.1. The impact of COVID-19 on economic activities and air quality

The overall strategy of the study is to compare the concentration of selected pollutants, economic activities, and other indicators in the same Lunar Calendar from 2018 to 2019. First, we present the various charts of traffic conditions and energy consumption during the COVID-19 outbreak, demonstrate the impact of COVID-19 on economic activities, and visually present the basic facts of air quality in China. The Wuhan Covid-19 lockdown was happening on January 23, 2020, and the 2020 Lunar New Year is January 25. So, in this study, the first day of the first lunar month and the Lantern Festival were taken as dividing points. The research period is divided into three parts: 10 days before the Lunar New Year, from the Lunar New Year to the Lantern Festival, and 13 days after the Lantern Festival.

2.2. Empirical results of the air quality from 2020 with that in 2018–2019

In the second step, after controlling the fixed effects of years, cities, and various meteorological factors, we examine the impact of the COVID-19 outbreak on each city and discuss the heterogeneous effects of the COVID-19 epidemic according to the proportion of secondary industry as represented by GDP and the cumulative number of confirmed cases in each city. The empirical model is as follows:

$$AQ_{it} = \beta_0 + \beta_1 yr dum_{2020} + \beta cont_{it} + \eta_i + \varepsilon_{it} \tag{1}$$

$$AQ_{it} = \beta_0 + \beta_1 year dum_{2020} + \beta_2 yr dum_{2019} + \beta cont_{it} + \eta_i + \varepsilon_{it} \tag{2}$$

Where the subscript *i* indicates the corresponding city, the subscript *t* indicates the corresponding year and AQ_{it} represents the air quality. Furthermore, *yr dum* is dummy variable representing the relative time window of the occurrence of COVID-19, and the subscript number is marked as the corresponding year. In addition, we also add other meteorological factors as control variables $cont_{it}$, mainly including temperature, wind force in daytime and nighttime, and it was raining, snowing or not to control the influence of meteorological factors on air quality. η_i represents city fixed effects. ε_{it} is a random disturbance term that changes with time. In the above reference groups, 2019 and 2018 are the two models, β_1

which is the coefficient of the $yr dum_{2020}$, the parameters of interest capture the changes in air quality after the COVID-19 outbreak compared with other periods.

2.3. The dynamic trend effect of the COVID-19 shock on air quality

The third step is to test the dynamic effect of the COVID-19 shock on air quality. Using event analysis, we used the Lunar New Year as the starting point and divided the period after the Spring Festival into 10 intervals. The dynamic trend effect of the COVID-19 shock was tested by the following method.

$$AQ_{it} = \beta_0 + \sum_{k=1}^{k=10} \beta_k \times D_{ik} + \eta_i + \beta_1 year dum_{2020} + \beta cont_{it} + \varepsilon_{it} \tag{3}$$

$$AQ_{it} = \beta_0 + \sum_{k=1}^{k=10} \beta_k \times D_{ik} + \eta_i + \beta_1 yr dum_{2020} + \beta_2 yr dum_{2019} + \beta cont_{it} + \varepsilon_{it} \tag{4}$$

D_{ik} is a series of time interval dummy variables referred to above, with values (0, 1) to control the interval between each day and the lunar new year. For example, $D_{2020,1}$ is the first dummy variable representing the first 3-day interval from the lunar new year in 2020. The data for 37 days after the Spring Festival are collected in this study. Therefore, it is divided into 10 interval periods. The coefficient of concern in the trend effect test was β_k , which represents differences in air quality between the COVID-19 period in 2020 and the reference years of 2018 or 2019 in the *k*-th period after the Lunar New Year, to characterize the dynamic change of air quality in the COVID-19 period and the previous year.

And we also use the interrupted time-series analysis (ITSA) method to identify the effects of Wuhan Covid-19 Lockdown on air pollution. First, there is no doubt that the Covid-19 epidemic outbreaking in Wuhan in the early of the 2020 year is exogenous to all cities in China. No city officials were able to anticipate the outbreak and take action in advance. So, we use a single-group to analyze the effects of Wuhan COVID-19 Lockdown. The standard ITSA regression model assumes the following form (Biglan et al., 2000; Briesacher et al., 2013; Huitema and Mckean, 2000; Muller, 2004).

$$AQ_t = \beta_0 + \beta_1 T_t + \beta_2 X_t + \beta_3 X_t T_t + \varepsilon_t \tag{5}$$

AQ_t is the aggregated air quality variable measured at each equally

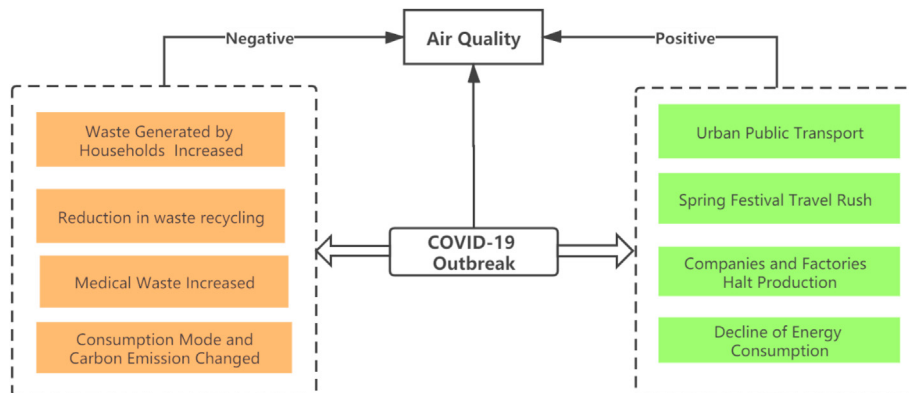


Fig. 1. A flow chart of the analysis in this study.

spaced time point t , T_t is the time since December 1, 2019, X_t is an indicator variable representing the intervention (Wuhan Lockdown on January 23, 2020), and $X_t T_t$ is an interaction term. In consideration of robustness, we used not only the day of the closure of the Wuhan but also five days before the lockdown point.

Secondly, we consider using two kinds of control groups for comparison and modify the single-group model to the multiple-group model.

$$AQ_t = \beta_0 + \beta_1 T_t + \beta_2 X_t + \beta_3 X_t T_t + \beta_4 Z + \beta_5 Z T_t + \beta_7 Z X_t T_t + \varepsilon_t \quad (6)$$

Here Z is a dummy variable to denote the cohort assignment (treatment or control group), and $Z T_t$, $Z X_t$, $Z X_t T_t$ are all interaction terms among previously described variables. A multiple-group ITSA may be particularly valuable when there is an exogenous policy shift that affects all the groups. The critical assumption is that the change in the level or trend in the outcome variable is presumed to be the same for the control group and, counterfactually, for the treatment group had it not received the intervention.

We consider two kinds of control groups. The first set of control group includes Chengdu, Chongqing, Hangzhou, and Shanghai. The reason for choosing these four cities as the closure of Wuhan is that the dimensions of these four cities are similar to Wuhan. The second control group selects Chongqing, Changsha, Nanchang, Hefei, Zhengzhou, and Xi'an cities. These six cities are the capital cities bordering Hubei Province.

3. Study area, measurement, and period

3.1. Sample selection

The Chinese Spring Festival was one of the most important traditional festivals in China. The peak transport in the Spring Festival season which was also referred to the "spring travel rush". During this period, extremely high traffic inflows and outflows occurred as numerous migrant residents return to their hometowns. Most people were recorded twice or more due to the round-trip and other trips they made in the Spring Festival season (Hu, 2019). The emission sources were expected to vary greatly during this time due to tremendous fluctuations in human activity (Huang et al., 2012). In China, the COVID-19 lockdown period began since 2020-01-23 and lasted until the end of February. This lockdown period overlapped with the Spring Festival season which included the Spring Festival and Lantern Festival. Traffic inflows and outflows in the Spring Festival season were concentrated before the Spring Festival and around the Lantern Festival. In order to ensure the comparability of the sample air quality from 2018 to 2020, a total of 31 megacities in mainland China were selected for research. Locations of these metropolises are demonstrated in Fig. 2. In the empirical research section, we use 1 day before the Spring Festival (Lunar New Year's Eve) to 13 days after the Lantern Festival as a research period.

Air quality is the core variable of this paper, and there are many evaluation methods for air quality. For example, according to the "environmental air quality standard" (GB 3095–2012) issued by the national Ministry of Environmental Protection, the basic items of air pollutants included SO_2 , PM_{10} , $PM_{2.5}$, and other three categories, in terms of index selection for measuring air pollution, some scholars have chosen AQI (Chen et al., 2012), $PM_{2.5}$, PM_{10} and SO_2 and soot (dust) emissions (Kleanthous et al., 2009; Lee et al., 2005; Troncoso et al., 2012) are taken as research indicators. Acknowledging that if single pollutant data is selected as the proxy variable of air quality, data coincidence will be challenging to avoid, and sulfur dioxide and particulate matter have always been the focus

data in air quality detection. $PM_{2.5}$, PM_{10} and SO_2 from January–February 2018 to January–February 2020 is selected as the main indicators of air quality and mainly derived from the national urban air quality real-time distribution platform of the China National Environmental Monitoring Centre (<http://www.cnemc.cn/>).

Besides, considering that meteorological conditions are the main factors affecting air quality through its influence on the diffusion, transmission, and accumulation of pollutants (Wang et al., 2009; Zhou et al., 2018). So, we control day and night temperature, day and night wind power, rain levels, snow levels. All such data is derived from the China meteorological website (<http://www.cma.gov.cn/>). Urban economic data is derived from the National Bureau of Statistics (<http://www.stats.gov.cn/>), and the number of confirmed cases of COVID-19 comes from the National Health Committee (<http://en.nhc.gov.cn/>).

3.2. Descriptive statistics

Table 1 shows the descriptive statistics of selected variables. The 2018, 2019 and 2020 columns present the mean values and standard deviation by years. Relative to 2018 and 2019, 2020 on average, has no significant difference in Meteorological conditions, and lower $PM_{2.5}$, PM_{10} , SO_2 , NO_2 . The literature suggests that rain and snow may wash away the air pollution (Olszowski, 2017). However, there is no significant difference in the proportion of rain and snow in the research sample over the last three years, with the lowest proportion in 2020 on average. 2020 average temperature is the lowest in the last three years, and the daytime wind speeds in 2020 are not the highest they have been in the last three years.

4. Results and discussions

4.1. Comparison of air quality between 2020 and 2018–2019 for the same lunar calendar

As mention above, we select the period January 15 to January 24, 2020, ten days before spring festive as the first stage; the period January 25 to February 8, 2020, fifteen days between Chinese New Year to Lantern Festival as the second stage; the period February 9 to February 22, 2020, fourteen days after Lantern Festival as the third stage. Then we have compared these periods with the historical corresponding lunar periods from 2018 to 2019. Fig. 3 depicts the three-stage scatter plot of the mean and confidence interval for the $PM_{2.5}$, PM_{10} and SO_2 . The mean of $PM_{2.5}$ in 2020 is $77.63 \mu\text{g}/\text{m}^3$ which is higher than in previous years in Stage 1. In Stage 2 the mean of $PM_{2.5}$ in 2020 is $60.58 \mu\text{g}/\text{m}^3$ which still is higher than that in 2019. However, the mean of $PM_{2.5}$ is $41.39 \mu\text{g}/\text{m}^3$ in Stage 3 which is significantly lower than that in previous years. For PM_{10} in 2020, the mean for Stage 1 and 2 are $92.76 \mu\text{g}/\text{m}^3$ and $68.19 \mu\text{g}/\text{m}^3$ which have no significant difference from 2019. However, the mean of PM_{10} is $58.12 \mu\text{g}/\text{m}^3$ in Stage 3 which is significantly lower than that in previous years. As for SO_2 , a similar pattern is observed.

In general, we find that there is no significant difference in air pollution levels in stage 1, while air pollution is significantly lower than in previous years in Stage 3. Air pollutants show a decreasing trend in 2020. In previous years, the air pollutant trend shows a "V" shape. Air pollutants arise with work resumption around the Lantern Festival after reaching their lowest point at stage 2. Fig. 3 show these results.

In addition to air pollutants, we also found that:

(1) *Subway passenger volume*. As the main form of urban transportation, the subway is often regarded as the "heart" of the city. Fig. B in the appendix shows the impact of COVID-19 on urban



Fig. 2. Map of the study area.

Table 1
Descriptive statistics.

Variable	Observations	2018		2019		2020	
		mean	Std. Dev.	mean	Std. Dev.	mean	Std. Dev.
PM _{2.5}	2697	56.78	42.27	61.52	50.67	51.32	44.37
PM ₁₀	2697	90.73	61.32	84.92	62.03	63.37	48.43
SO ₂	2697	18.56	15.55	13.16	10.5	11.27	8.72
O ₃	2697	59.11	18.77	46.27	17.33	58.75	15.16
NO ₂	2697	38.68	17.96	36.18	19.61	22.69	12.8
Temperature	2697	13.34	8.39	8.82	8.3	8.62	7.7
Rain and Snow (ratio)	2694	18.80%		29.25%		18.35%	
Wind Speed	2697	3.25	0.54	1.95	0.92	2.31	1.19

Note: Rain and Snow (ratio) statistic is the proportion of rain or snow days during the research period in each year.

subway traffic. On average, the mean values of *subway passenger volume* (Ten Thousand) are 358.46, 376.22, and 426.17 in stage 1; 477.15, 363.11, and 48.15 in stage 2; and 477.15, 511.98, and 58.65 in stage 3. It is apparent that after the Spring Festival in 2020, subway passenger volumes in the five cities decline precipitously. In later lockdown periods when the city closed the subway, passenger volumes approach zero. This decline is more prominent compared to the same period in the previous years, suggesting that the lockdown measures significantly impacted urban residents' choice of the subway as a transportation mode. Urban public transportation is not the first choice for people who wanted to travel during the outbreak, and it is halted when incidences become severe.

(2) *Urban congestion index*. This is an accurate indicator of road traffic conditions in cities (Requia et al., 2018). Fig. C in the appendix shows the impact of COVID-19 on urban road traffic conditions.

There is no significant difference between the congestion index in stage 1 of 2020 and the previous years—1.47 (2018), 1.34 (2019), and 1.33 (2020). Due to the nationwide lockdown measures, the stage 2 congestion index in 2020 is quite different from that of 2019 and 2018. On average, Stage 2 congestion indices were 1.37 (2018), 1.31 (2019), and 1.1 (2020). In stage 3, after the Lantern Festival in 2018 and 2019, the congestion index returns to the average levels experienced before the Spring Festival but remains at low levels throughout 2020. On average, Stage 3 congestion indices are 1.72 (2018), 1.63 (2019), and 1.13 (2020). Therefore, we may draw preliminary conclusions based on the trends of subway passengers and the urban congestion index: the lockdown measures caused by COVID-19 significantly reduced people's travel and particularly their use of public and other means of transportation.

(3) *Daily average coal consumption*: Coal is an essential factor affecting air quality and is one of the primary sources of SO₂. We

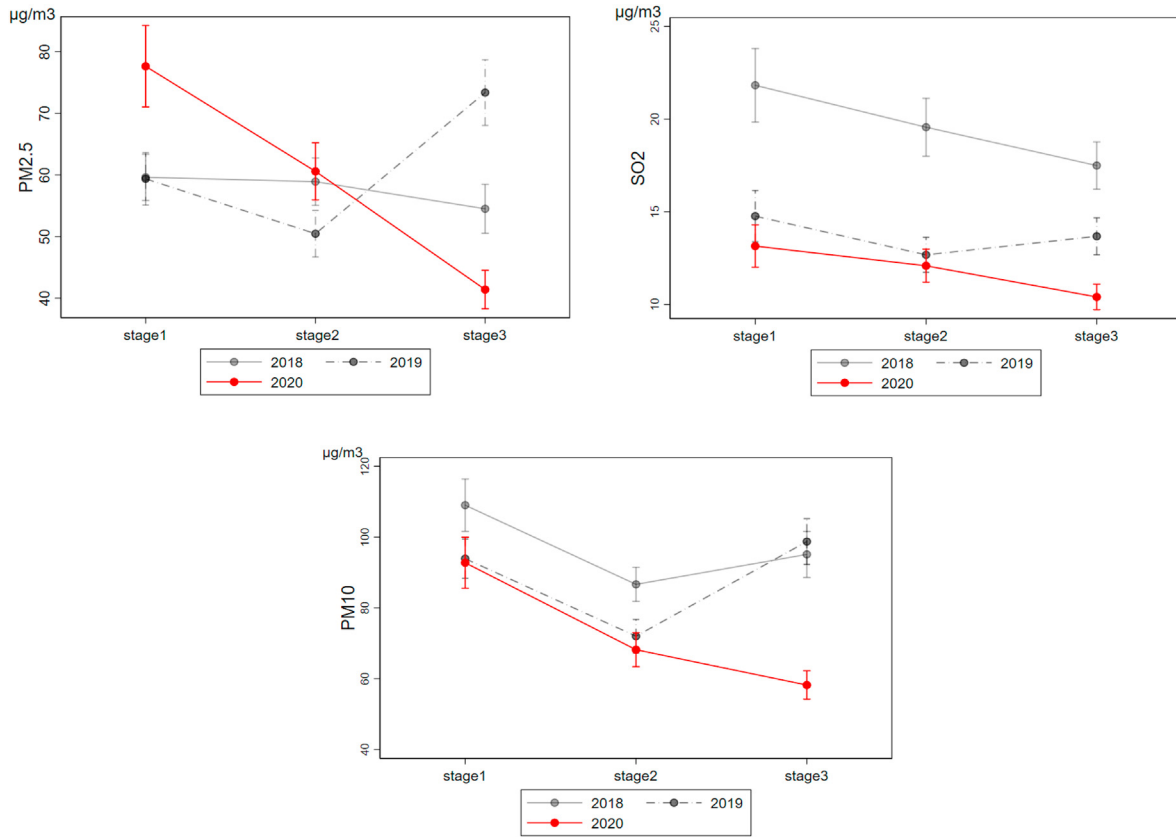


Fig. 3. Three stages of average air quality (PM_{2.5}, PM₁₀, SO₂) status from 2018 to 2020.

make an approximate comparison of the daily average coal consumption of the six power plants between the Lunar New Year and the Lunar Lantern Festival from 2018 to 2020 (Fig. D in the appendix). The results show that no significant difference between the first stage of 2020 and that of previous years. In contrast, the daily average coal consumption in 2020 decrease significantly after the Spring Festival, from 450,000 tons to 350,000 tons per day, approximately 22% in the second and third stages. Possible explanations are that many heavy industries with high coal consumption postponed returning to work due to the COVID-19, resulting in considerable changes in their coal consumption.

4.2. Baseline estimation

Table 2 presents the COVID-19 lockdown measures effects on air quality upon the baseline model specification (1) and (2). The benchmark group in the columns (1) to (3) is 2018, and columns (4) to (6) is 2019. All columns consist of the city-level meteorological conditions, including temperature, wind force in daytime and nighttime, and raining or not. Besides, city fixed effect is included. Standard errors presented in the parenthesis are clustered at the city level.

The coefficients for 2020.Year are negative and statistically significant at the 1% level for PM₁₀ and SO₂ in columns (2) to (3). These mean that PM₁₀ and SO₂ in the 2020 research period are statistically significantly lower than in 2018. The estimated coefficients of -15.28 and -6.55 indicate that the lockdown measures in 2020 lead to a 15.28 and 6.55 decline in PM₁₀ and SO₂ compare to 2018. In other words, after controlling for meteorological condition and city fixed effects, relative to the average, PM₁₀ dropped by 19.18% and SO₂ dropped by 45.71% in 2020. The coefficients for 2020.Year are

negative and statistically significant at the 1% level for PM_{2.5}, PM₁₀ and SO₂ in columns (4) to (6). These mean that three air pollutant indicators in the 2020 research period are statistically significantly lower than in 2019. The estimated coefficient of -7.4, -19.34 and -1.41 indicate that the lockdown measures in 2020 lead to a 7.4 µg/m³, 19.34 7.4 µg/m³ and 1.41 7.4 µg/m³ decline compared to 2019. In other words, after controlling for meteorological condition and city fixed effects, relative to the average, PM_{2.5} drops by 13.13%, PM₁₀ drops by 24.28% and SO₂ decreases by 9.84%. Whether using 2018 or 2019 as the benchmark group, the overall air pollutant levels in 2020 show a significant decline.

4.3. Dynamic estimation

In the benchmark regression analysis, we regard 2020 as a whole and estimate the effects of COVID-19 on air pollution. To estimate the dynamic effect of COVID-19 on air pollution levels in 2020, the interactive term of time to Spring Festival(t) and 2020.Year dummy variables are added to the baseline regression equation. Time to Spring Festival is treated as a continuous variable to measure the timing trend effect of air quality with the increase of distance in time to the Spring Festival, and the results are shown in Table 3.

In Table 3 the variable t represents the date from the Spring Festival. For example, if t equals 10, this means ten days after Spring Festival. The variable 2020.Year × t represents a year dummy variable multiplied by the variable t. The coefficients for 2020.Year × t are negative and statistically significant at the 1% level in columns (1), (2) and (4) to (6), indicating that the further away from Spring Festival, the greater decline in air pollutant levels. The benchmark group in columns (1) to (3) is 2018, and in columns (4) to (6) is 2019.

Table 2
Benchmark regression Results.

	2018 Year is base group			2019 Year is base group		
	(1)	(2)	(3)	(1)	(2)	(3)
	PM _{2.5}	PM ₁₀	SO ₂	PM _{2.5}	PM ₁₀	SO ₂
2019.Year	7.097** (2.59)	4.334 (1.17)	-5.130*** (-6.27)			
2020.Year	-0.461 (-0.18)	-15.279*** (-4.26)	-6.552*** (-8.09)	-7.399*** (-4.22)	-19.336*** (-9.71)	-1.412*** (-5.60)
Wind Speed	Y	Y	Y	Y	Y	Y
Rain Dummy	Y	Y	Y	Y	Y	Y
Temperature	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y
Obs.	2694	2691	2694	1798	1796	1798
Adjusted R ²	0.403	0.473	0.657	0.427	0.463	0.698

Note: The values in brackets are standard deviations; 2. ***, **, * respectively indicate the significance at the statistical level of 1%, 5% and 10%; 3. heteroscedasticity is considered in all models, and statistical inference is made by using standard error of robustness (the same as in the following table); 4. The base group listed in (1)-(3) is in 2018, and (4)-(6) take 2019 as the base group, and Y represents YES that means these variables are controlled in estimation.

Taking column (2) as an example, after adding year fixed effect and city fixed effect, each day after the Spring Festival, the PM₁₀ level drops by 1.13 per day. These findings indicate that COVID-19 lockdown measures contribute to a significant decline in air pollutants. During our research period, the longer the time from the lockdown started, the more significant the air pollution reduction was.

To test whether there is heterogeneity in the dynamic trend effect during the lockdown measures period, this study specifies models (3) and (4). We split the continuous variable t mentioned above into 9 intervals. Each interval contains three days. Table 4 represents the corresponding results. The benchmark group in columns (1) to (3) is 2019, and in columns (4) to (6) is 2018. Fig. 4 depicts the scatter plots of the estimate coefficients for lockdown measures dynamic effects and the corresponding confidence intervals. Fig. 4 has three subgraphs: 2018 vs. 2019, 2020 vs. 2018, and 2020 vs. 2019 of three air pollutant indicators. From Table 4 and Fig. 3, we find that: First, the air pollutant levels have increased in 2019 relative to 2018. Second, Compared with 2018 and 2019, a dynamic downward trend in air pollution levels due to lockdown measures in 2020 relative to 2018 and 2019. Third, the dynamic trend effects brought by lockdown measures present obvious heterogeneity. In the 6 and 8 intervals during the Lantern Festival, the decline in air pollution levels was the largest and statistically significant. At the beginning of lockdown measures, in the first few intervals, there was no significant difference between the air pollution levels in 2020 and previous years. Due to China's urban-rural structure and labor migration habits, around the Lantern Festival is the peak period for labor to return to work. Combining Table A in appendix and Fig. 3, there is no significant difference between PM_{2.5} in 2020 and previous years in the early stage, but PM_{2.5} around the Lantern Festival is significantly lower than that in previous years. This further validates the human economic activities have a significant impact on air pollution.

In this part of the empirical analysis, 2018 and 2019 are replaced as different reference groups. The year 2020 is compared with the same Lunar Calendar of the previous two years. Based on the estimation results, we conclude that the COVID-19 lockdown measures have a significant positive impact on air quality in China's main cities. In addition, the further away from the Spring Festival, the better the air quality in 2020. In the literature, we learned that the COVID-19 outbreak had a considerable impact on people's daily economic activities. Water, land, and air traffic, as well as subway passenger traffic, energy consumption, and so on, demonstrated precipitous declines. The source of air pollution, in addition to objective natural factors, was human-made pollution sources, which primarily included industrial waste, gas, coal-fired chimneys, and road traffic (motor vehicles, ships, etc.) The outbreak reduced the generation of human-made pollution sources and effectively improved air quality.

4.4. Heterogeneity analysis

First, the heterogeneity of the industrial structure is examined. PM_{2.5} and PM₁₀ are mainly derived from combustion smoke and dust and secondary pollutants, and SO₂ is primarily derived from coal-fired power plants, industrial furnaces, etcetera. Power generation and steel are two industries that consume considerable amounts of coal (Lu et al., 2013). Therefore, the industry that has the greatest impact on air quality is the secondary industry, which primarily includes the mining industry, manufacturing industry, electricity, heat, gas and water production and supply industry, construction industry, etc. The lockdown measures had a significant impact on the secondary industry by delaying the resumption of work.

Therefore, according to the value-added of the secondary industry accounted for GDP, the major cities in China are divided into

Table 3
Continues dynamic effect of COVID-19 on air Quality.

	Base Group 2018			Base Group 2019		
	(1) PM _{2.5}	(2) PM ₁₀	(3) SO ₂	(1) PM _{2.5}	(2) PM ₁₀	(3) SO ₂
2020.Year	26.754*** (4.45)	14.292* (2.00)	-6.962*** (-4.41)	42.845*** (7.81)	17.397** (2.70)	1.296 (1.45)
t	-0.885*** (-5.77)	-0.295 (-1.48)	-0.240*** (-5.45)	0.228 (1.58)	0.233 (1.27)	-0.072* (-2.51)
2019.Year×t	1.134*** (5.48)	0.399 (1.48)	0.150** (2.91)	0.000 (.)		
2020.Year×t	-0.994*** (-4.55)	-1.132*** (-4.14)	0.041 (0.81)	-2.115*** (-10.10)	-1.546*** (-6.13)	-0.114*** (-3.42)
Wind Speed	Y	Y	Y	Y	Y	Y
Rain Dummy	Y	Y	Y	Y	Y	Y
Temperature	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Obs.	2694	2691	2694	1798	1796	1798
Adjusted R ²	0.447	0.486	0.670	0.479	0.481	0.711

Note: 2020.Year is a binary indicator for year 2020, taking a value of one if the years is 2020, and zero otherwise. t is a continuous variable representing days after the Spring Festival. The standard errors in parenthesis are clustered at the province level. *, **, and *** represent statistical significance levels at the 10%, 5%, and 1%, respectively, and Y represents YES that means these variables are controlled in estimation.

three categories: low, medium, and high. Table 5 presents the heterogeneity of the industrial structure effects on COVID-19 lockdown measures. All columns consist of the city-level meteorological conditions, including temperature, wind force in daytime and nighttime, and it is raining or not. Besides, the city fixed effect and year fixed effect are included. Standard errors presented in the parenthesis are clustered at the city level. Columns (1) to (3) represent the estimation of cities with relatively low secondary industry proportions, columns (4) to (6) represent medium proportion cities, and columns (7) to (9) represent high proportion cities. Estimates show significant city heterogeneity for both PM₁₀ and SO₂. This indicates that the decrease in air pollutants due to COVID-19 is more remarkable in cities with a higher proportion of value-added by the secondary industry. Taking the PM₁₀ indicator as an example, in the low group, lockdown measures led to a decrease in PM₁₀ of 10.5 µg/m³, but in the high group, the corresponding decline in PM₁₀ was 20.3 µg/m³. There were notable differences between the two groups.

Second, the heterogeneity of the cumulative number of confirmed cases in provinces is also investigated. In addition to the heterogeneity of the industrial structure, the heterogeneity of the cumulative number of confirmed cases in each province also affected local precise and differentiated epidemic control strategies. The differences in the cumulative number of confirmed cases will affect people's daily lives, which will further affect the effect of COVID-19 lockdown measures on air pollutants. Next, based on the cumulative number of confirmed cases of COVID-19 released by the National Health and Health Commission as of February 21, 2020, our sample is divided into three groups. Table 6 represents the

heterogeneity of the cumulative confirmed cases of effects. Estimates show a group that is more severely affected by the COVID-19 epidemic, the more significant the reduction in air pollution levels. Estimates show significant city heterogeneity for both PM₁₀ and SO₂. This indicates that the decrease in air pollutants due to COVID-19 is more remarkable in cities with a higher proportion of value-added by the secondary industry. Taking the PM₁₀ indicator as an example, in the low group, lockdown measures led to a decrease in PM₁₀ of 10.5 µg/m³, but in the high group, the corresponding decline in PM₁₀ was 20.3 µg/m³. There are notable differences between the two groups.

4.5. Interrupted time-series analysis (ITSA)

Table B and Fig E in the appendix have reported the estimation of the model (5) and (6), which also show the air pollution tendency. Posttreatment trend estimations that are the estimated coefficient of β₁ + β₃ for the single-group model and the treatment group, control group, difference for the multiple-group model. Column (1) reports the single-group results. The starting level of the air pollution PM_{2.5} was estimated at 106 and PM_{2.5} appeared to decrease significantly every day from December 1, 2019, to January 23, 2020. We also found after the introduction of the Wuhan lockdown policy, PM_{2.5} significantly daily reduced at a rate of 1.12 (95% CI = [-1.84,-0.41]). Column (2) reports the robustness check results. We use January 19, 2020, as the intervention date, the Postintervention Linear Trend of Wuhan lockdown is -1.63 (95% CI = [-2.34,-0.93]). These indicate if COVID-19 is an exogenous shock, under the single-group model, the Wuhan lockdown policy

Table 4
Interval dynamic effect of COVID-19 on air Quality.

	2019 VS. 2020			2018 VS. 2020		
	(1)	(2)	(3)	(1)	(2)	(3)
	PM _{2.5}	PM ₁₀	SO ₂	PM _{2.5}	PM ₁₀	SO ₂
2020.Year	17.04* (2.35)	-9.213 (-1.11)	0.789 (0.66)	1.638 (0.23)	-13.46 (-1.74)	-10.24*** (-4.72)
2020-1 Interval	9.269 (1.07)	22.10* (2.28)	-1.651 (-1.19)	9.777 (1.13)	16.77 (1.85)	5.13* (2.25)
2020-2 Interval	-10.53 (-1.22)	6.012 (0.62)	-1.657 (-1.22)	19.44* (2.31)	24.20** (2.72)	5.38* (2.51)
2020-3 Interval	-16.92* (-2.09)	-2.630 (-0.28)	-1.185 (-0.87)	-14.84 (-1.83)	-14.25 (-1.68)	1.83 (0.84)
2020-4 Interval	-17.35* (-2.12)	-0.0664 (-0.01)	-2.455 (-1.82)	-1.857 (-0.23)	1.141 (0.13)	5.99** (2.84)
2020-5 Interval	-43.72*** (-4.69)	-32.05** (-2.98)	-1.859 (-1.40)	3.050 (0.37)	-3.131 (-0.34)	6.94** (3.17)
2020-6 Interval	-43.57*** (-4.79)	-29.61** (-2.81)	-5.56*** (-3.73)	-2.438 (-0.30)	0.445 (0.05)	3.629 (1.65)
2020-7 Interval	-56.14*** (-6.32)	-42.50*** (-4.30)	-2.814 (-1.96)	-34.05*** (-4.37)	-39.16*** (-4.47)	1.215 (0.57)
2020-8 Interval	-40.71*** (-4.80)	-18.36 (-1.72)	-1.910 (-1.38)	-20.31* (-2.31)	-12.68 (-1.22)	3.534 (1.67)
2020-9 Interval	-36.29*** (-4.07)	-11.39 (-1.09)	-3.926** (-2.75)	-2.028 (-0.24)	-7.724 (-0.63)	5.949** (2.63)
Wind Speed	Y	Y	Y	Y	Y	Y
Rain Dummy	Y	Y	Y	Y	Y	Y
Temperature	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Obs.	1798	1796	1798	1795	1794	1795
Adjusted R ²	0.513	0.525	0.722	0.465	0.521	0.696

Note: Due to layout reasons, we do not report the results of 2018 vs. 2019. The core coefficients and their confidence intervals are shown in Fig. 4. The standard errors in parenthesis are clustered at the province level. *, **, and *** represent statistical significance levels at the 10%, 5%, and 1%, respectively.

has significantly reduced air pollution levels. Column (3) reports the multiple-group model estimated results of first type control groups. Postintervention Linear Trend of treated group (Wuhan) is -1.13 (95% CI = [-1.94, -0.32]), correspondingly control groups are -0.06 (95% CI = [-0.61, 0.49]), the difference between treated and control group is -1.07 (95% CI = [-2.05, -0.09]). That means that compared with the capital cities of a similar dimension, the air pollution in Wuhan has dropped more after the lockdown. Column (5) reports the multiple-group model estimated results of second type control groups. The difference between Wuhan and control groups is 0.672 (95% CI = [-0.73, 2.08]), so the difference is not significant. This result may imply that the provinces surrounding Wuhan may also have adopted strict control regulations so that there was no significant difference between the control and treatment groups.

5. Discussion

This study shows that, compared to 2018 and 2019, the

lockdown measures caused by the COVID-19 significantly affected air pollutants in 31 megacities in mainland China. Furthermore, the dynamic and heterogeneity analyses indicate that after the Spring Festival, air quality increasingly improved in 2020. A higher proportion of secondary industries and a larger number of confirmed cases resulted in a more significant decline in air pollutants. Our results are consistent with much of the recent literature (Lian et al., 2020; Wang et al., 2020; Zheng et al., 2020), although they notably differ from those of (Pei et al., 2020; Zambrano-Monserrate et al., 2020). Reasons for this inconsistency in the existing literature may include: First, part of the literature only studies three cities in China, while this study covers 31 cities, and the research objects are broader; Second, the reference group of this study is from the same Lunar period, whereas certain studies use the equivalent Gregorian period—considering the Chinese New Year effect, using the lunar calendar is a more reasonable choice.

A key contribution of this study, compared to the existing literature, is our exploration of the dynamic effects of lockdown measures on air pollution. Considering the Spring Festival travel

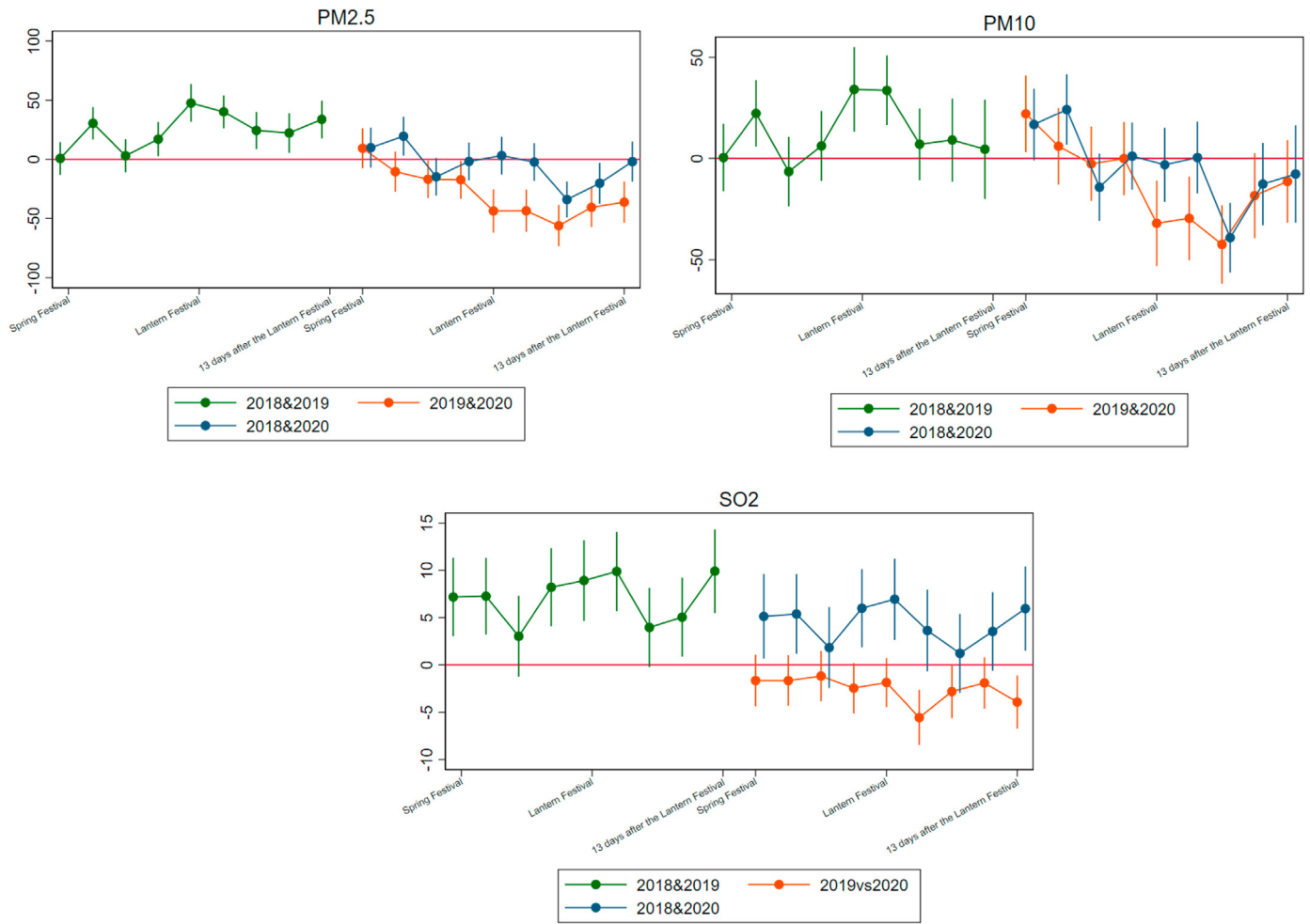


Fig. 4. The coefficients plots of Interval Dynamic Effect of COVID-19 on Air Quality.

rush in China, we used the time period up to the Lunar New Year to measure the dynamic effect, and the empirical results verify the impact of the decline in human economic activity on air pollution. Another contribution of this study is that it explores the impact of the heterogeneity of cities and the cumulative number of confirmed cases of air pollution. The existing literature on the impact of COVID-19 on air quality mostly focuses on factors such as geographical location and meteorological conditions, while ignoring the economic structure and severity of the epidemic (Collivignarelli et al., 2020; Mahato et al., 2020; Sharma et al., 2020).

Unfortunately, we cannot determine the long-term effects on air quality from this data—long-term effects of lifestyle behavioral changes, such as the lack of physical activity, alcohol use, mask wearing, increased handwashing, and a greater willingness to drive private cars (Aloi et al., 2020) are worthy of further exploration. Additionally, the indirect effect of lockdown measures on air quality was beyond the scope of this study. Quarantine policies, established in most countries, have led consumers to increase their demand for online shopping for home delivery. Consequently, waste generated by households has increased. Medical waste is also on the rise (Zambrano-Monserrate et al., 2020). These indirect effects caused by COVID-19 are worthy of future research.

6. Conclusions and implications

Using the city-level daily panel data of 31 cities in mainland China during the 2018–2020 lunar calendar, we conduct an empirical study on the effects of the COVID-19 lockdown measures on urban air quality. The empirical results show the following:

First, the COVID-19 lockdown measures have severely affected everyday life. Subway passenger traffic volumes and the urban road congestion index reflect urban transportation habits. Due to strict prevention and control measures, the subway was closed, passenger traffic volume ceased, and the congestion index dropped to 1 after the Spring Festival indicating that people reduced their frequency of trips. The decrease in the daily average coal consumption of approximately 22% demonstrated the delayed resumption of work in factories.

Second, we controlled for meteorological factors such as daytime and nighttime wind, temperature, and dummy variables for rainfall, city, and year fixed effects during the equivalent lunar period. Then, compared to 2018, PM₁₀ in 2020 dropped by 15.28 μg/m³ and SO₂ dropped by 6.55 μg/m³; Compared to 2019, PM_{2.5} dropped by 7.4 μg/m³, PM₁₀ dropped by 19.34 μg/m³, and SO₂ dropped by 1.41 μg/m³. The improvement in air quality is both quantitative and statistically significant. The results of further analysis of heterogeneity show that the proportion of secondary industries and the cumulative number of confirmed cases have a

Table 5
Heterogeneity effects of industrial structure.

	Low			Medium			High		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
	PM _{2.5}	PM ₁₀	SO ₂	PM _{2.5}	PM ₁₀	SO ₂	PM _{2.5}	PM ₁₀	SO ₂
2020.Year	0.04 (0.01)	-10.50* (-2.00)	-4.62*** (-5.83)	0.19 (0.03)	-14.07* (-2.10)	-7.38*** (-5.78)	-2.18 (-0.55)	-20.38** (-3.04)	-8.31*** (-3.90)
Wind Speed	Y	Y	Y	Y	Y	Y	Y	Y	Y
Rain									
Dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
Temperature	Y	Y	Y	Y	Y	Y	Y	Y	Y
Wind Speed	Y	Y	Y	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	957	956	957	868	868	868	869	867	869
Adjusted R ²	0.384	0.465	0.708	0.383	0.462	0.596	0.437	0.452	0.657

Note: Low represents the bottom 33% of the secondary industry samples; Medium represents the middle 33% of the secondary industry samples; High represents the top 33% of the secondary industry samples; The standard errors in parenthesis are clustered at the province level. *, **, and *** represent statistical significance levels at the 10%, 5%, and 1%, respectively. Y represents YES that means these variables are controlled in estimation.

Table 6
Heterogeneity effects of cumulative number of confirmed cases.

	Low cases			Medium cases			High cases		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
	PM _{2.5}	PM ₁₀	SO ₂	PM _{2.5}	PM ₁₀	SO ₂	PM _{2.5}	PM ₁₀	SO ₂
2020.Year	3.201 (0.61)	-	-	-1.284 (-0.26)	-8.788 (-1.80)	-7.384*** (-5.78)	-6.514 (-1.77)	-	-
Wind Speed	Y	Y	Y	Y	Y	Y	Y	Y	Y
Rain Dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
Temperature	Y	Y	Y	Y	Y	Y	Y	Y	Y
Wind Speed	Y	Y	Y	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	957	957	957	868	867	868	869	867	869
Adjusted R ²	0.363	0.331	0.708	0.464	0.574	0.596	0.404	0.493	0.657

Note: The standard errors in parenthesis are clustered at the province level. *, **, and *** represent statistical significance levels at the 10%, 5%, and 1%, respectively. Y represents YES that means these variables are controlled in estimation.

noteworthy impact on lockdown measures. The empirical findings of this study provide a novel understanding of COVID-19 lockdown measures. There is an apparent improvement in urban environmental performance in the short term, such as pollution reduction by the transportation and industrial sectors. The results of dynamic empirical studies provide robust evidence for the conclusion that as more time lapses after the initiation of the lockdown, the reduction in air pollution becomes cumulatively more significant. The long-term impact on environmental sustainability, however, requires

further assessment.

Based on our empirical results, several practical implications are presented. First, policymakers should promote remote working for specific businesses. In terms of environmental protection and air management, the existing literature often discusses the role of external policies—such as number limitation and emission reduction—the impacts of which are limited and only effective in the short term. As a sudden external shock, the COVID-19 outbreak led to reductions in travel and factory emissions. The pandemic has

resulted in people reconsidering the possibility of remote working as businesses face a bleak set of options—continue business as usual but with the risk of grave illness, shut down the business, or transition to working from home.

In China, remote work and online classes became a daily part of social life during the crisis. In some situations, remote working has been shown to improve employee productivity (Bloom et al., 2015), and be a catalyst for creating more inclusive workplaces (Mas and Pallais, 2017). Business heterogeneity will greatly affect the adaptability of remote work as not all businesses can transition to remote work, although businesses in industries with higher income and better-educated employees may be more likely to achieve this. This is also worthy of further research.

Second, policymakers need to promote investment in new infrastructure. The interconnected, intelligent world has made telecommuting and remote classes possible. Remote working requires significant investment in new infrastructure to allow for high-speed network access to foster increased efficiencies. Infrastructure upgrades will also benefit the industrial sector by, among others, establishing an intelligent transportation system through AI technology to reduce air pollution and optimize waste recycling, establish an intelligent water supply management system using 5G technology to reduce hydrological risk, and utilize digital twin technology to mitigate the risk of disasters to effectively improve the levels of environmental assessment and resilience of industrial development.

CRediT authorship contribution statement

Jian Zhang: Writing – original draft, Software, Validation, Visualization, Formal analysis, Conceptualization, Methodology. **Houjian Li:** Methodology, Writing – review & editing, Supervision. **Muchen Lei:** Conceptualization, Methodology. **Lichen Zhang:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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References

Aloi, A., Alonso, B., Benavente, J., Cordera, R., Echániz, E., González, F., Ladisa, C., Lezama-Romanelli, R., López-Parra, Á., Mazzei, V., Perrucci, L., Prieto-Quintana, D., Rodríguez, A., Sañudo, R., 2020. Effects of the COVID-19 lockdown on urban mobility: empirical evidence from the city of santander (Spain). *Sustainability* 12, 3870. <https://doi.org/10.3390/su12093870>.

Athey, S., Imbens, G.W., 2017. The state of applied econometrics: causality and policy evaluation. *J. Econ. Perspect.* 31, 3–32. <https://doi.org/10.1257/jep.31.2.3>.

Biglan, A., Ary, D., Wagenaar, A.C., 2000. The value of interrupted time-series experiments for community intervention research. *Prev. Sci.* 1, 31–49. <https://doi.org/10.1023/A:1010024016308>.

Bloom, N., Liang, J., Roberts, J., Ying, Z.J., 2015. Does working from home work? Evidence from a Chinese experiment. *Q. J. Econ.* 130, 165–218. <https://doi.org/10.1093/qje/qju032>.

Briesacher, B.A., Soumerai, S.B., Zhang, F., Toh, S., Andrade, S.E., Wagner, J.L., Shoaibi, A., Gurwitz, J.H., 2013. A critical review of methods to evaluate the impact of FDA regulatory actions. *Pharmacoepidemiol. Drug Saf.* 22, 986–994. <https://doi.org/10.1002/pds.3480>.

Chan, K.L., Hartl, A., Lam, Y.F., Xie, P.H., Liu, W.Q., Cheung, H.M., Lampel, J., Pöhler, D., Li, A., Xu, J., Zhou, H.J., Ning, Z., Wenig, M.O., 2015. Observations of tropospheric NO₂ using ground based MAX-DOAS and OMI measurements during the Shanghai World Expo 2010. *Atmos. Environ.* 119, 45–58. <https://doi.org/10.1016/j.atmosenv.2015.08.041>.

Chan, K.L., Wang, Z., Ding, A., Heue, K.-P., Shen, Y., Wang, J., Zhang, F., Shi, Y., Hao, N., Wenig, M., 2019. MAX-DOAS measurements of tropospheric NO₂ and HCHO in Nanjing and a comparison to ozone monitoring instrument observations. *Atmos. Chem. Phys.* 19, 10051–10071. <https://doi.org/10.5194/acp-19-10051-2019>.

Chen, Y., Jin, G.Z., Kumar, N., Shi, G., 2013. The promise of Beijing: evaluating the impact of the 2008 Olympic Games on air quality. *J. Environ. Econ. Manag.* 66, 424–443. <https://doi.org/10.1016/j.jeem.2013.06.005>.

Chen, Y., Jin, G.Z., Kumar, N., Shi, G., 2012. Gaming in air pollution data? Lessons from China. *B E J. Econ. Anal. Pol.* 13. <https://doi.org/10.1515/1935-1682.3227>.

Collivignarelli, M.C., Abbà, A., Bertanza, G., Pedrazzani, R., Ricciardi, P., Carnevale Miino, M., 2020. Lockdown for CoViD-2019 in Milan: what are the effects on air quality? *Sci. Total Environ.* 732, 139280. <https://doi.org/10.1016/j.scitotenv.2020.139280>.

Dong, K., Sun, R., Dong, X., 2018. CO₂ emissions, natural gas and renewables, economic growth: assessing the evidence from China. *Sci. Total Environ.* 640–641, 293–302. <https://doi.org/10.1016/j.scitotenv.2018.05.322>.

Feng, L., Liao, W., 2016. Legislation, plans, and policies for prevention and control of air pollution in China: achievements, challenges, and improvements. *Journal of Cleaner Production, Preventing Smog Crises* 112, 1549–1558. <https://doi.org/10.1016/j.jclepro.2015.08.013>.

Feng, Y., Ning, M., Lei, Y., Sun, Y., Liu, W., Wang, J., 2019. Defending blue sky in China: effectiveness of the “air pollution prevention and control action plan” on air quality improvements from 2013 to 2017. *J. Environ. Manag.* 252, 109603. <https://doi.org/10.1016/j.jenvman.2019.109603>.

Galindo, N., Varea, M., Gil-Moltó, J., Yubero, E., Nicolás, J., 2011. The influence of meteorology on particulate matter concentrations at an urban mediterranean location. *Water Air Soil Pollut.* 215, 365–372. <https://doi.org/10.1007/s11270-010-0484-z>.

Hausman, C., Rapson, D.S., 2018. Regression discontinuity in time: considerations for empirical applications. *Annual Review of Resource Economics* 10, 533–552. <https://doi.org/10.1146/annurev-resource-121517-033306>.

He, C., Han, L., Zhang, R.Q., 2016. More than 500 million Chinese urban residents (14% of the global urban population) are imperiled by fine particulate hazard. *Environ. Pollut.* 218, 558–562. <https://doi.org/10.1016/j.envpol.2016.07.038>.

Hu, M., 2019. Visualizing the largest annual human migration during the Spring Festival travel season in China. *Environ. Plann.* 51, 1618–1621. <https://doi.org/10.1177/0308518x19845908>.

Huang, K., Zhuang, G., Lin, Y., Wang, Q., Fu, J., Zhang, R., Li, J., Deng, C., Fu, Q., 2012. Impact of Anthropogenic Emission on Air Quality over a Megacity – Revealed from an Intensive Atmospheric Campaign during the Chinese Spring Festival. *Faculty Publications and Other Works – Civil & Environmental Engineering*.

Huitema, B.E., Mckean, J.W., 2000. Design specification issues in time-series intervention models. *Educ. Psychol. Meas.* 60, 38–58. <https://doi.org/10.1177/00131640021970358>.

Kleanthous, S., Bari, MdA., Baumbach, G., Sarachage-Ruiz, L., 2009. Influence of particulate matter on the air quality situation in a mediterranean island. *Atmospheric Environment, Urban Air Quality* 43, 4745–4753. <https://doi.org/10.1016/j.atmosenv.2008.06.025>.

Kong, S., Li, X., Li, L., Yin, Y., Chen, K., Yuan, L., Zhang, Y., Shan, Y., Ji, Y., 2015. Variation of polycyclic aromatic hydrocarbons in atmospheric PM_{2.5} during winter haze period around 2014 Chinese Spring Festival at Nanjing: insights of source changes, air mass direction and firework particle injection. *Sci. Total Environ.* 520, 59–72. <https://doi.org/10.1016/j.scitotenv.2015.03.001>.

Lai, J., Pan, J., 2020. China's city network structural characteristics based on population flow during spring festival travel rush: empirical analysis of “tencent migration” big data. *J. Urban Plann. Dev.* 146, 04020018. [https://doi.org/10.1061/\(ASCE\)UP.1943-5444.0000581](https://doi.org/10.1061/(ASCE)UP.1943-5444.0000581).

Lee, B.-K., Jun, N.-Y., Lee, H.K., 2005. Analysis of impacts on urban air quality by restricting the operation of passenger vehicles during Asian Game events in Busan, Korea. *Atmos. Environ.* 39, 2323–2338. <https://doi.org/10.1016/j.atmosenv.2004.11.044>.

Li, J., Liao, H., Hu, J., Li, N., 2019. Severe particulate pollution days in China during 2013–2018 and the associated typical weather patterns in Beijing-Tianjin-Hebei and the Yangtze River Delta regions. *Environ. Pollut.* 248, 74–81. <https://doi.org/10.1016/j.envpol.2019.01.124>.

Li, J., Ye, Q., Deng, X., Liu, Yaolin, Liu, Yanfang, 2016. Spatial-temporal analysis on spring festival travel rush in China based on multisource big data. *Sustainability* 8, 1184. <https://doi.org/10.3390/su8111184>.

Li, X., Qiao, Y., Zhu, J., Shi, L., Wang, Y., 2017. The “APEC blue” endeavor: causal effects of air pollution regulation on air quality in China. *J. Clean. Prod.* 168, 1381–1388. <https://doi.org/10.1016/j.jclepro.2017.08.164>.

Lian, X., Huang, J., Huang, R., Liu, C., Wang, L., Zhang, T., 2020. Impact of city lockdown on the air quality of COVID-19-hit of Wuhan city. *Sci. Total Environ.* 742, 140556. <https://doi.org/10.1016/j.scitotenv.2020.140556>.

Linden, A., 2015. Conducting interrupted time-series analysis for single- and

- multiple-group comparisons. *STATA J.* 15, 480–500. <https://doi.org/10.1177/1536867X1501500208>.
- Lu, Q., Zheng, J., Ye, S., Shen, X., Yuan, Z., Yin, S., 2013. Emission trends and source characteristics of SO₂, NO_x, PM₁₀ and VOCs in the pearl river delta region from 2000 to 2009. *Atmospheric environment, improving regional air quality over the pearl river delta and Hong Kong: from. Sci. Pol.* 76, 11–20. <https://doi.org/10.1016/j.atmosenv.2012.10.062>.
- Mahato, S., Pal, S., Ghosh, K.G., 2020. Effect of lockdown amid COVID-19 pandemic on air quality of the megacity Delhi, India. *Sci. Total Environ.* 730, 139086 <https://doi.org/10.1016/j.scitotenv.2020.139086>.
- Mas, A., Pallais, A., 2017. Valuing alternative work arrangements. *Am. Econ. Rev.* 107, 3722–3759. <https://doi.org/10.1257/aer.20161500>.
- Miao, Z., Baležentis, T., Shao, S., Chang, D., 2019. Energy use, industrial soot and vehicle exhaust pollution—China's regional air pollution recognition, performance decomposition and governance. *Energy Econ.* 83, 501–514. <https://doi.org/10.1016/j.eneco.2019.07.002>.
- Muller, A., 2004. Florida's motorcycle helmet law repeal and fatality rates. *Am. J. Publ. Health* 94, 556–558. <https://doi.org/10.2105/AJPH.94.4.556>.
- Neidell, M., 2010. Air quality warnings and outdoor activities: evidence from Southern California using a regression discontinuity design. *J. Epidemiol. Community Health* 64, 921–926. <https://doi.org/10.1136/jech.2008.081489>.
- Olszowski, T., 2017. Comparison of PM₁₀ washout on urban and rural areas. *Ecological Chemistry and Engineering S* 24, 381–395. <https://doi.org/10.1515/eces-2017-0025>.
- Pei, Z., Han, G., Ma, X., Su, H., Gong, W., 2020. Response of major air pollutants to COVID-19 lockdowns in China. *Sci. Total Environ.* 743, 140879 <https://doi.org/10.1016/j.scitotenv.2020.140879>.
- Peretto, P.F., Valente, S., 2015. Growth on a finite planet: resources, technology and population in the long run. *J. Econ. Growth* 20, 305–331.
- Requia, W.J., Higgins, C.D., Adams, M.D., Mohamed, M., Koutrakis, P., 2018. The health impacts of weekday traffic: a health risk assessment of PM_{2.5} emissions during congested periods. *Environ. Int.* 111, 164–176.
- Sharma, S., Zhang, M., Anshika-Gao, J., Zhang, H., Kota, S.H., 2020. Effect of restricted emissions during COVID-19 on air quality in India. *Sci. Total Environ.* 728, 138878 <https://doi.org/10.1016/j.scitotenv.2020.138878>.
- The State Council of the People's Republic of China, 2013. Air pollution prevention and control action plan. http://www.gov.cn/zwqk/2013-09/12/content_2486773.htm.
- The State Council of the People's Republic of China, 2018. Three-year action plan to win the blue sky Defense war. http://www.gov.cn/zhengce/content/2018-07/03/content_5303158.htm.
- Troncoso, R., de Grange, L., Cifuentes, L.A., 2012. Effects of environmental alerts and pre-emergencies on pollutant concentrations in Santiago, Chile. *Atmos. Environ.* 61, 550–557. <https://doi.org/10.1016/j.atmosenv.2012.07.077>.
- Wang, P., Guo, H., Hu, J., Kota, S.H., Ying, Q., Zhang, H., 2019. Responses of PM_{2.5} and O₃ concentrations to changes of meteorology and emissions in China. *Sci. Total Environ.* 662, 297–306. <https://doi.org/10.1016/j.scitotenv.2019.01.227>.
- Wang, S., Li, Q., Fang, C., Zhou, C., 2016. The relationship between economic growth, energy consumption, and CO₂ emissions: empirical evidence from China. *Sci. Total Environ.* 542, 360–371. <https://doi.org/10.1016/j.scitotenv.2015.10.027>.
- Wang, S., Xing, J., Zhao, B., Jang, C., Hao, J., 2014. Effectiveness of national air pollution control policies on the air quality in metropolitan areas of China. *J. Environ. Sci.* 26, 13–22. [https://doi.org/10.1016/S1001-0742\(13\)60381-2](https://doi.org/10.1016/S1001-0742(13)60381-2).
- Wang, W., Primbs, T., Tao, S., Simonich, S.L.M., 2009. Atmospheric particulate matter pollution during the 2008 Beijing olympics. *Environ. Sci. Technol.* 43, 5314–5320. <https://doi.org/10.1021/es9007504>.
- Wang, Y., Yuan, Y., Wang, Q., Liu, C., Zhi, Q., Cao, J., 2020. Changes in air quality related to the control of coronavirus in China: implications for traffic and industrial emissions. *Sci. Total Environ.* 731, 139133 <https://doi.org/10.1016/j.scitotenv.2020.139133>.
- Yu, M., Zhu, Y., Lin, C.-J., Wang, S., Xing, J., Jang, C., Huang, Jizhang, Huang, Jinying, Jin, J., Yu, L., 2019. Effects of air pollution control measures on air quality improvement in Guangzhou, China. *J. Environ. Manag.* 244, 127–137. <https://doi.org/10.1016/j.jenvman.2019.05.046>.
- Yue, H., He, C., Huang, Q., Yin, D., Bryan, B.A., 2020. Stronger policy required to substantially reduce deaths from PM 2.5 pollution in China. *Nat. Commun.* 11, 1462. <https://doi.org/10.1038/s41467-020-15319-4>.
- Zambrano-Monserrate, M.A., Ruano, M.A., Sanchez-Alcalde, L., 2020. Indirect effects of COVID-19 on the environment. *Sci. Total Environ.* 728, 138813 <https://doi.org/10.1016/j.scitotenv.2020.138813>.
- Zhang, H., Wang, Shuxiao, Hao, J., Wang, X., Wang, Shulan, Chai, F., Li, M., 2016. Air pollution and control action in Beijing. *Journal of Cleaner Production, Preventing Smog Crises* 112, 1519–1527. <https://doi.org/10.1016/j.jclepro.2015.04.092>.
- Zheng, H., Kong, S., Chen, N., Yan, Y., Liu, D., Zhu, B., Xu, K., Cao, W., Ding, Q., Lan, B., Zhang, Z., Zheng, M., Fan, Z., Cheng, Y., Zheng, S., Yao, L., Bai, Y., Zhao, T., Qi, S., 2020. Significant changes in the chemical compositions and sources of PM_{2.5} in Wuhan since the city lockdown as COVID-19. *Sci. Total Environ.* 739, 140000 <https://doi.org/10.1016/j.scitotenv.2020.140000>.
- Zhou, C., Wei, G., Xiang, J., Zhang, K., Li, C., Zhang, J., 2018. Effects of synoptic circulation patterns on air quality in Nanjing and its surrounding areas during 2013–2015. *Atmospheric Pollution Research* 9, 723–734. <https://doi.org/10.1016/j.apr.2018.01.015>.
- Zhu, N., Zhang, D., Wang, W., Li, X., Yang, B., Song, J., Zhao, X., Huang, B., Shi, W., Lu, R., Niu, P., Zhan, F., Ma, X., Wang, D., Xu, W., Wu, G., Gao, G.F., Tan, W., 2020. A novel coronavirus from patients with pneumonia in China, 2019. *N. Engl. J. Med.* <https://doi.org/10.1056/NEJMoa2001017>.