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Original Research

The Impact of City Lockdown and Air Pollution on the Spread of Covid-19

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Abstract

Considering the high variability of Covid-19 and unknown sequelae of rebound infections. We may be caught in a long-term struggle against the virus. The evaluation and summary of past anti-epidemic policies highlight profound practical significance for either decision makers or individuals. This paper applies both theoretical and empirical approaches to study the impact of city lockdown and air pollution on Covid-19. First, we apply an extended Susceptible-Infected-Removed (SIR) model to identify the relationship between lockdown, air pollution, and Covid-19 cases. Second, we apply the Differences-in-Differences (DID) model and Poisson Pseudo-Maximum Likelihood (PPML) model to test the impact of lockdown on Covid-19, by sorting out lockdown policies implemented by cities during the epidemic. Third, we empirically analyze the impact of air pollution on Covid-19, based on daily data from 257 cities in China. Finally, we examine the mechanism by which lockdown impacts Covid-19. Newly confirmed Covid-19 cases are reduced by 31.1% nationwide (excluding Wuhan) during the lockdown period. Regions with lower air pollution experience fewer Covid-19 cases. Air pollution aggravates Covid-19, with the pollutants PM2.5, PM10, NO2, CO, and O3 having the greatest impact. The results indicate that an increase in one unit of air quality index (AQI) concentrations is associated with 1.723 more newly confirmed cases. The effects of air pollution on the spread of Covid-19 diminish as the population size increases. Lockdown can inhibit the spread of Covid-19 by reducing air pollution and population movement.

Keywords: city lockdown, air pollution, migration, Covid-19

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Introduction

Covid-19 has killed more than 6.9 million people worldwide and caused significant economic losses. Today, although the World Health Organization has downgraded the public health event level of the Covid-19, it does not mean that the Covid-19 has ended completely. According to Academician of the Chinese Academy of Sciences Zhong Nanshan[1], second round of infection in China will peak at the end of June, with the number of infections likely to reach 65 million per week. Considering the high variability of Covid-19 and unknown sequelae of rebound infections. We may be caught in a long-term struggle against the virus. The prevention and treatment of Covid-19 should still be highly valued, and relevant experience should also be systematically sorted out and summarized. Among them, the lockdown policy deserves more attention as the most important means to combat the spread of the virus in the early stages.

After the first case of Covid-19 in Wuhan, China was confirmed in early December 2019, the Chinese government introduced a lockdown policy in Wuhan on January 23, 2020. By isolating confirmed cases, tracking contacts, suspending public transportation, canceling public events, closing schools and entertainment facilities, and establishing checkpoints, the lockdown policy effectively limited the spread of Covid-19 early in the outbreak. Since then, the Chinese government had launched public health emergency measures in all provinces. Eventually, the Chinese government's epidemic prevention and control work had shifted quickly from curbing the domestic spread of Covid-19 to preventing inbound infections and a domestic resurgence.

At present, the majority of the literature supports the conclusion that lockdown suppresses the spread of Covid-19 [1, 2]. However, in terms of the composition of the lockdown-related articles, most of them belong to comparative and forecasting studies, which mainly use mathematical modeling, simulation, descriptive statistics and other methods to predict the changes in the Covid-19 epidemic that lockdown may lead to. However, the specific impact of lockdown policy on the changes in the Covid-19 epidemic still needs normative public policy evaluation research to elaborate. Moreover, the related public policy research focuses on the mechanism of human mobility and pays little attention to other mechanisms.

In addition to blocking population migrations, the lockdown produces perceived improvements in air quality [3]. The temporary closure of many shops and enterprises during the lockdown led to sharp declines in industrial activities and vehicle use, leading to improved air quality in the lockdown cities. He et al. (2020) [4] find that the air quality index (AQI) and weekly SO2 concentration drop by 19.4% and 13.9 ug/m3, respectively, in lockdown cities compared to cities that do not lockdown. The lockdown restricts residential activities and lowers consumption, effectively reducing air pollution [5, 6]. Based on a study in Wuhan, Cole et al. (2020a) [3] find that the Wuhan lockdown led to a noticeable decline in SO_2 and PM10 concentrations.

Furthermore, air pollutants, as carriers of virus transmission, may affect epidemic transmission between people [7]. Some studies have found that air pollution is significantly associated with Covid-19 cases and deaths [8]. Studies have shown that bad environmental conditions would lead to an increase in mortality in the mid-term of the Wuhan outbreak and not only directly but indirectly affect the spread of the epidemic by affecting the average humidity [9]. Two studies conducted in California (USA) and the Netherlands also found a high positive correlation between air pollution and Covid-19 cases [10, 11]. However, the spread of Covid-19 is closely related to the location, transmission route, and infected population of the epidemic. Areas with severe air pollution are not necessarily areas with severe epidemic transmission. The Covid-19 may spread in areas with better air quality, as these areas are closer to the initial outbreak site [12]. This makes it even more necessary to incorporate air pollution mechanisms into public policy evaluation systems to distinguish factors such as distance and air pollution. Thus, air pollution itself is not only likely to affect the spread of Covid-19, but also an important mechanism for lockdown affecting the spread of Covid-19, nevertheless, the existing articles are rarely involved.

We also find that there is a lack of quantitative analysis of the impact of lockdown policy on the spread of Covid-19 in different scenarios in the existing public policy evaluation studies. For example, whether there are differences in the impact of lockdown under different severity of the epidemic, different city sizes, and different levels of air pollution. Furthermore, there is potential for further improvement in the econometric methods used in existing Covid-19-related policy evaluation research. For example, the data set of the dependent variables usually contains a large number of zero values, which may lead to a serious biased estimation problem.

Given the background above, we establish an extended SIR model to analyze the theoretical mechanism underlying how the lockdown impacts Covid-19, and propose hypotheses. Using lockdown as a quasi-natural experiment, we set up cities with lockdown as a treatment group and cities without lockdown as a control group and applied the difference-in-differences (DID) model and the Poisson Pseudo-Maximum Likelihood (PPML) estimator (rather than the OLS estimator) to explore the implementation effect of lockdown. Furthermore, assuming air pollution can accelerate the incidences of Covid-19, in addition to having a direct effect on Covid-19, the lockdown may

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[1] From Mr Zhong Nanshan's speech at The Greater Bay Area Science Forum (2023)

have also indirectly contained the spread of Covid-19 by reducing air pollution. To test these ideas, we use daily air quality index (AQI) data from 20 January to 20 February 2020 published by the China Environmental Monitoring Centre to assess the impact of air pollution on the spread of Covid-19. We use panel quantile regression and grouping regression to analyze the heterogeneity of different epidemic severity levels and different pollutants. Finally, we investigate whether the lockdown reduces the spread of Covid-19 by lowering air pollution, reducing both inter-city and intra-city migration.

The rest of this paper is organized as follows: Section 2 introduces the theoretical mechanism and research hypothesis. Section 3 describes our data and methodology. Section 4 reports our results and Section 5 examines the mediating mechanism of our results. Section 6 discusses and concludes.

Theoretical Model and Hypothesis

We apply the extended SIR model used by Pindyck (2020) [13] and Chudik et al. (2020) [2] to contain the variable of death and to account for the effect of air pollution and lockdown on Covid-19. The extended SIR model is written as formula 1.

$$P = S_t + I_t + R_t + D_t \tag{1}$$

where P denotes the total population size of a region. The model assumes P is a constant value and consists of four different types of people: S, I, R, and D; St refers to people who have not yet been infected with Covid-19 during the t period. Because of the risk of infection, they are also called susceptible people; It refers to people who have been infected with Covid-19 during the t period; Rt refers to people who have recovered; Dt denotes people who have died. We assume that people who have recovered from Covid-19 would be no longer susceptible.

To explore the impact of lockdown on the epidemic, we apply the method used by Chudik et al. (2020) [2]. The P in Eq. (1) is divided into two groups: Pl is the fraction of the population that is healthy and has been isolated; P_e is the fraction of the population exposed to Covid-19. We assume that the risk of getting infected with Covid-19 is low for people who have been isolated. Therefore, the model associated with the lockdown is written as:

$$P_e = \delta P = S_t + I_t + R_t + D_t \tag{2}$$

where δ is the proportion of P_e to P. The expression 1-δ measures the level of lockdown enforcement. Cities with a higher value of 1-δ implement stricter lockdown measures. A value of δ = 1 indicates the city has no lockdown.

We not only consider lockdown in the model, but also put air pollution into the model as an influencing factor. Air pollution can accelerate the spread of the epidemic, decrease the rate of recovery, and increase the death rate [8-11]. We perform a series of differential equation transformations based on Eq. (1) and Eq. (2) to obtain the function of the relationship between confirmed cases, lockdown and air pollution. We finally get a second-order nonlinear difference equation as:[2]

$$i_{t+1} = \frac{i_t^{\,2}}{i_{t-1}} + \frac{a\beta}{\delta}[i_t i_{t-1}(1 - \frac{\gamma_r}{a} - a\gamma_d) - i_t^{\,2}] \tag{3}$$

where it = It/P; β is the contact rate of Covid-19, which depends on the biological nature of the Covid-19 virus and which we assume does not change with time or place; γr and γd are the recovery rate and the death rate, respectively; a is the impact coefficient of air pollution. We consider aβ, γ_r/a, and aγ_d to be the actual contact rate, the actual recovery rate, and the actual death rate of Covid-19, respectively, under the influence of air pollution.

We assume the initial value of i1 and i2 are functions of δ in Eq. (3). This yields:

$$i_1(\delta) = \frac{\delta}{1000},\quad i_2(\delta) = [1 + \frac{a\beta}{\delta}(\delta - \frac{\delta}{1000}) - (\frac{\gamma_r}{a} + a\gamma_d)]\frac{\delta}{1000} \tag{4}$$

In order to analyze Eq. (3) and Eq. (4) more vividly, Fig. 1 and Fig. 2 show the estimated results of Eq. (3) and Eq. (4) graphically, where the ordinate represents the proportion of confirmed cases and the abscissa represents time.

To examine the effect of the lockdown on the spread of Covid-19, we assume that the actual contact rate, the recovery rate, the death rate, and the air pollution level are symmetrical. We assume that β = 0.21 [13], γ_r = 0.0686, γ_d = 0.0014 [14, 15], and a = 1.25 and set different δ value to simulate the spread of Covid-19 in Eq. (3). Fig. 1 shows the simulation results. We set three δ values: δ = 1, δ = 0.75, and δ = 0.5. In this situation, the corresponding implementation strengths (1-δ) are 0, 0.25, and 0.5, respectively. The expression 1-δ = 0 represents the situation without any lockdown measures. Fig. 1 shows that the peak of the Covid-19 infected cases curve reaches the highest level in cities where there was no lockdown. As the strength of city-specific lockdown measures increases, the peak gradually decreases. Therefore, we propose the following hypothesis:

Hypothesis 1: Implementing a lockdown effectively curbs the spread of Covid-19. Cities implementing stronger lockdown better curb the spread of Covid-19.

To examine the effect of air pollution on Covid-19, we analyze the spread of Covid-19 under different air pollution levels, assuming that the actual contact rate

[2] See Appendix for the derivation process.

($a\beta$), the recovery rate (γ_r/a), the death rate ($a\gamma_d$), and the strength of lockdown implementation are symmetrical. First, we assume that $\beta = 0.21$, $\gamma_r = 0.0686$, $\gamma_d = 0.0014$, and $\delta = 0.5$, and set different a values to simulate the spread of Covid-19 using Eq. (3). The simulation results are shown in Fig. 2. We set three a value: a = 1, a = 1.25, and a = 1.5. The expression a = 1 signifies there is no air pollution; a>1 means there is air pollution in the city, with higher values associated with more serious air pollution. Fig. 2 shows that the time distribution (it) of Covid-19 infected cases is relatively flat. As the air pollution increases, the peak of Covid-19 infected cases gradually increases, with a faster peak period. This leads to Hypothesis 2:

Hypothesis 2: Air pollution accelerates the rate of Covid-19 spread and exacerbates the degree of spread. Cities with more serious air pollution have a higher rate and degree of Covid-19 spread.

Methodology

Difference-in-Differences Model

We first examine the impact of lockdown on the spread of Covid-19, considering the lockdown to be a quasi-natural experiment. Cities that implement lockdown are the treatment group; and cities that do not implement lockdown are the control group. Each city

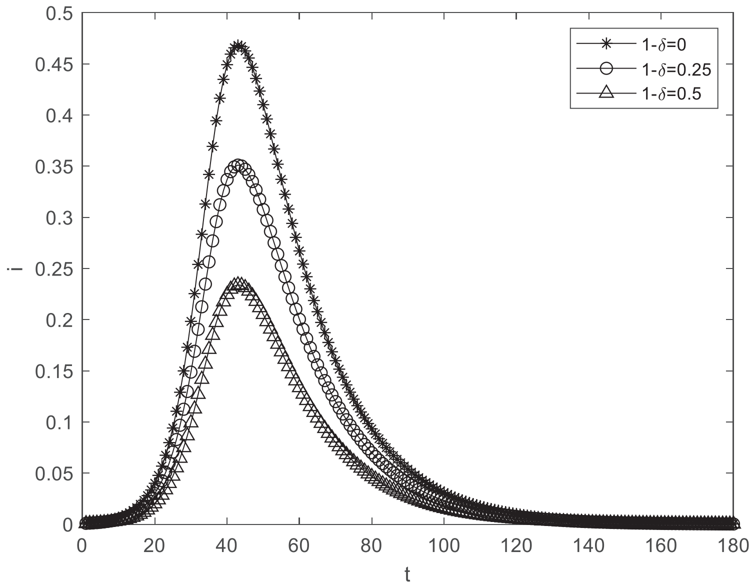

Fig. 1. The simulation of Covid-19 under different lockdown strength.

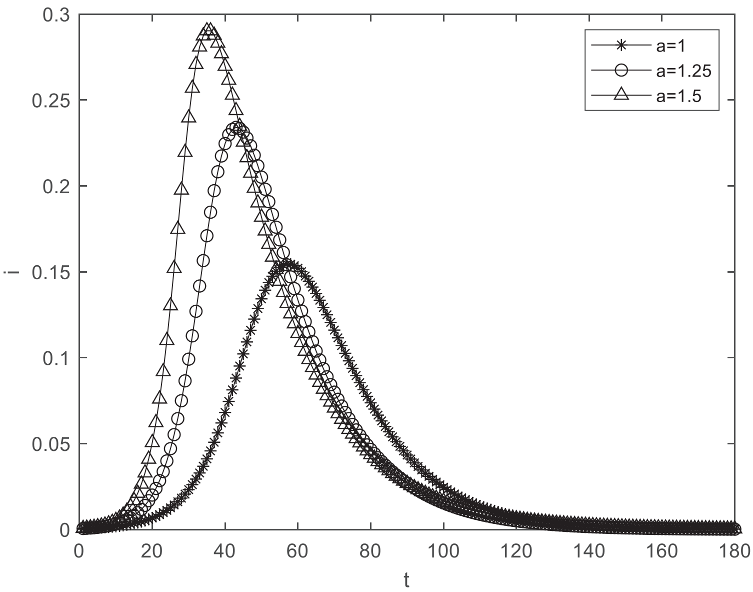

Fig. 2. The simulation of Covid-19 under different air pollution levels.

implementing a lockdown at different time points, so we establish a continuous-time difference-in-differences (DID) model, specified in Eq. (5).

$$INC_{it} = \alpha_0 + \beta_1 CL_{it} \times TIME_{it} + \lambda_j \sum_{j=1}^{n} Z_{jit} + v_i + u_t + \varepsilon_{it} \tag{5}$$

where i refers to cities; t is the date. INC denotes the daily Covid-19 case count. CL is a dummy variable representing the presence of a lockdown during the study window: if city i implemented a lockdown between 20 January and 20 February 2020, CL is set as 1; if not, it is set as 0. TIME is the time dummy variable: if city i implements a lockdown at time t, the variable is set as 1 from time t; otherwise, it is set as 0. Z is the set of control variables, including the temperature, rainfall, distance from Wuhan, the construction of rail traffic, economic development level, and population density. vi represents province fixed effects; ut represents time fixed effects; and εit represents random error term.

There are many zero values in the dependent variable (INC); as such, we draw on the research of Zhang et al. (2020) [16] and apply a Poisson Pseudo-Maximum Likelihood (PPML) approach for the robustness test.

Panel Quantile Regression Model

A quantile regression describes the different effects of air pollution on different levels of Covid-19 and comprehensively shows the distribution of the impact of air pollution on the spread of Covid-19. This approach is more stable compared to a traditional regression on outlier handling, as it can estimate the conditional median and other conditional quantiles of the dependent variables (INC); in contrast, the traditional regression estimates the conditional average only. Hence, we apply a panel quantile regression model as follows:

$$Q_{NC_{it}}(\tau \mid X_{it}) = \alpha_i + \ln X_{it}^{T} \beta(\tau) + \varepsilon_{it}, i = 1,2,...,N, t = 1,2,...,T \tag{6}$$

where α_i represents the fixed effect, which does not change with the variation in quantile. X_{it} represents the dependent variables, including the key dependent variable lnAQI, and the set of control variables Z, which change with the variation of quantile. τ denotes the quantile. ε_{it} is a random error term.

Data and Summary Statistics

Data

We collect city-level daily data of 257 Chinese cities between 20 January and 20 February 2020. The analysis relies on city-level Covid-19 case data provided by the database of Harvard University in the United States[3]. As the Covid-19 outbreak in China is first reported in Wuhan city, the prevalence pattern is different in Wuhan compared to other cities. After the middle of January, the confirmed cases of Covid-19 increased exponentially, due to inadequate medical resources. This may have contributed to a more severe delay and measurement errors in the number of Wuhan's confirmed cases. Wuhan data are removed to eliminate this bias. In addition, we analyze the nationwide sample without cities in Hubei province, and analyze the Hubei province sample without Wuhan to increase the robustness of the empirical results.

The dependent variable is the Covid-19 (INC), measured using newly confirmed Covid-19 cases. The key independent variables are lockdown (CL) and air pollution (AQI). When modelling the relationship between lockdown, air pollution and Covid-19, a series of control variables are set, categorize as climate, distance from Wuhan (lndis), the availability of urban rail transit (urt), and demographic and economic-related variables. To assess the mediating effect of lockdown on Covid-19, we select AQI, the daily move-in migration index of a city (MI), and the daily within-city migration index of a city (WC) as the mediating variables. We discuss Covid-19, lockdown and mediating variables data, and each category of control variables in the following subsections.

Covid-19

Fig. 3 illustrates the changes in the numbers of newly confirmed Covid-19 cases from 20 January to 20 February 2020, and shows that the daily new case count increased rapidly after 20 January, peaking on 3-5 February. The new daily case count then trended downward and stabilized after 20 February. Due to statistical method changes, Hubei Province began to include clinically diagnosed cases as newly confirmed cases starting on 12 February. Thus, the newly confirmed Covid-19 case count in other cities in Hubei significantly increased on that day. However, the effect of that change can be removed from empirical research using time-fixed effects [17].

Lockdown

Since the Covid-19 outbreak, many cities in China have implemented diverse lockdown policies to restrict population movement and slow the spread of the epidemic. There are three types of lockdowns: (1) all transport in and out of the city is shut down; (2) household-based outdoor activities are restricted (including the closure of all public transportation, the prohibition of all private cars except for special permits, and the prohibition of public gatherings); (3) enclosed

[3] Database of Harvard University, see https://projects.iq.harvard.edu/chinadatalab.

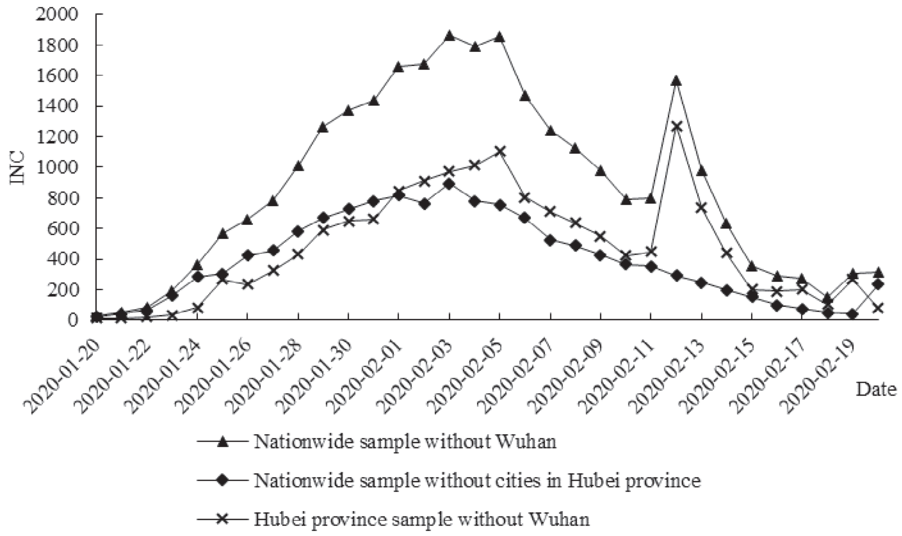

Fig. 3. Time trend of average newly confirmed Covid-19 cases.

community management [3]. The types and timing of the three lockdown policies are listed in Table 1[4]. A city implementing any of these lockdown policies is classified as effective, that is, CL = 1; otherwise, CL = 0.

Based on the research of Li et al. (2020) [7], air pollution is measured using the daily air quality index (AQI) published by the China National Environmental Monitoring Centre. In addition, we analyze pollutant differences using data for six air pollutants ($PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, O_3). The scale and intensity of population movement have an important impact on the spread of Covid-19. As the dominant search engine in China, "Baidu migration data" reports the real-time population movements of a city, including the "daily move-in migration index of a city (MI)", and a "daily within-city migration index of a city (WC)" [3]. We collect the indexes of MI and WC between 20 January and 20 February 2020. A city with higher MI and WC indexes indicates that the population movement between and within the city is more frequent and the population movement intensity is greater. The data of MI and WC are collected from the "Harvard Dataverse".

Figs 4-6 show the time trends for AQI, MI, and WC between 20 January and 20 February 2020. All three variables experienced a decreasing trend after lockdown implementation on 20 January 2020. This indicates that implementing the lockdown significantly reduces both air pollution and population movement. Among them, the air pollution in Hubei province sample without Wuhan showed a slight upward trend between 3 February and 5 February. This is related to the climate during the period. After 3 February, the weather in Hubei Province changed from cloudy to sunny. In addition, in sunny weather, the daily activities of residents increased, which caused the air pollution level to rise slightly. After 5 February, there was heavy rainfall in Hubei, and the air pollution level dropped. However, the effect of that change can be removed from empirical research using time-fixed effects and introducing climate control variables [17].

Climate

We use data on the daily average temperature (tem), 24 h accumulated precipitation (pre) and relative humidity (humi) to control the effects of climate on the spread of Covid-19. Data on three variables are collected from the National Meteorological Information Center's "Chinese Surface Climate Data Day Value Data Set (V3.0)". The temperature, precipitation, and humidity may have impacted the epidemic by influencing residential social activities and the media of spread [17]. For example, the Covid-19 virus can survive longer in lower temperatures [18]. Increased rainfall may reduce residential outdoor activities. Low air humidity might increase the stability of Covid-19 virus and favor its transmission [19]. These factors affect the spread of Covid-19.

Distance from Wuhan

Cities that are closer geographically to Wuhan are more likely to have close connections through population flows and economic exchanges with Wuhan, the city with the first confirmed Covid-19 case. Statistics indicate that before the Wuhan lockdown from 11 to 23 January, almost 4.3 million people flowed from Wuhan to the rest of China [20], significantly increasing the risk of spreading the epidemic. The outflow population from Wuhan is more likely to flow into cities closer to Wuhan, increasing the risk of spreading

[4] This study established the lockdown start date and implementation period for each city using Wikipedia data. See https://en.wikipedia.org/wiki/ Covid-19_pandemic_ lockdown_ in_ Hubei.

Table 1. Timetable for the implementation of lockdown in Chinese cities.

City	Province	The time for implementation	City	Province	The time for implementation
Transport shutdown			Zhengzhou	Henan	2020-2-4
Wuhan	Hubei	2020-1-23	Zhumadian	Henan	2020-2-4
Huanggang	Hubei	2020-1-23	Linyi	Shandong	2020-2-4
Ezhou	Hubei	2020-1-23	Harbin	Heilongjiang	2020-2-4
Xiaogan	Hubei	2020-1-24	Nanjing	Jiangsu	2020-2-4
Jingzhou	Hubei	2020-1-24	Xuzhou	Jiangsu	2020-2-4
Suizhou	Hubei	2020-1-24	Changzhou	Jiangsu	2020-2-4
Huangshi	Hubei	2020-1-24	Nantong	Jiangsu	2020-2-4
Yichang	Hubei	2020-1-24	Zhenjiang	Jiangsu	2020-2-4
Jingmen	Hubei	2020-1-24	Fuzhou	Fujian	2020-2-4
Xianning	Hubei	2020-1-24	Jingdezhen	Jiangxi	2020-2-4
Shiyan	Hubei	2020-1-24	Haikou	Hainan	2020-2-5
Tianmen	Hubei	2020-1-24	Sanya	Hainan	2020-2-5
Qianjiang	Hubei	2020-1-24	Kunming	Yunnan	2020-2-5
Xiantao	Hubei	2020-1-24	Qingdao	Shandong	2020-2-5
Shennongjia	Hubei	2020-1-27	Jinan	Shandong	2020-2-5
Xiangyang	Hubei	2020-1-28	Taian	Shandong	2020-2-5
Household-based outdoor restrictions			Rizhao	Shandong	2020-2-5
Huanggang	Hubei	2020-2-1	Nanchang	Jiangxi	2020-2-5
Wenzhou	Zhejiang	2020-2-2	Hefei	Anhui	2020-2-5
Taizhou	Zhejiang	2020-2-2	Nanning	Guangxi	2020-2-5
Fangchenggang	Guangxi	2020-2-2	Shijiazhuang	Hebei	2020-2-5
Yulin	Guangxi	2020-2-2	Yangzhou	Jiangsu	2020-2-5
Xian	Shaanxi	2020-2-2	Taizhou	Jiangsu	2020-2-5
Bengbu	Anhui	2020-2-3	Suqian	Jiangsu	2020-2-5
Huaibei	Anhui	2020-2-3	Yancheng	Jiangsu	2020-2-5
Binzhou	Shandong	2020-2-3	Liaoning	Liaoning	2020-2-6
Hangzhou	Zhejiang	2020-2-4	Jiangxi	Liaoning	2020-2-6
Ezhou	Hubei	2020-2-4	Jilin	Jilin	2020-2-6
Fuzhou	Fujian	2020-2-4	Maanshan	Anhui	2020-2-6
Xuzhou	Jiangsu	2020-2-4	Zhuhai	Guangdong	2020-2-6
Jingdezhen	Jiangxi	2020-2-4	Yaan	Sichuan	2020-2-6
Harbin	Heilongjiang	2020-2-4	Neijiang	Sichuan	2020-2-6
Zhumadian	Henan	2020-2-4	Suzhou	Jiangsu	2020-2-6
Ningbo	Zhejiang	2020-2-5	Hubei	Hubei	2020-2-7
Taizhou	Jiangsu	2020-2-5	Anhui	Anhui	2020-2-7
Hefei	Anhui	2020-2-5	Tianjin	Tianjin	2020-2-7
Fuyang	Anhui	2020-2-5	Guangzhou	Guangdong	2020-2-7
Benxi	Liaoning	2020-2-5	Shenzhen	Guangdong	2020-2-7

Table 1. Continued.

Liuzhou	Guangxi	2020-2-5	Lanzhou	Gansu	2020-2-7
Guilin	Guangxi	2020-2-5	Chengdu	Sichuan	2020-2-7
Hechi	Guangxi	2020-2-5	Suining	Sichuan	2020-2-7
Jiangxi	Jiangxi	2020-2-6	Guangyuan	Sichuan	2020-2-7
Xianyang	Shaanxi	2020-2-6	Guiyang	Guizhou	2020-2-7
Jinzhou	Liaoning	2020-2-6	Tangshan	Hebei	2020-2-7
Changchun	Jilin	2020-2-6	Lianyungang	Jiangsu	2020-2-7
Tangshan	Hebei	2020-2-7	Ziyang	Sichuan	2020-2-8
Tianjin	Tianjin	2020-2-9	Foshan	Guangdong	2020-2-8
Hubei	Hubei	2020-2-16	Deyang	Sichuan	2020-2-9
Enclosed community management			Mianyang	Sichuan	2020-2-9
Chongqing	Chongqing	2020-1-31	Huizhou	Guangdong	2020-2-9
Wuzhong	Ningxia	2020-1-31	Dongguan	Guangdong	2020-2-9
Yinchuan	Ningxia	2020-1-31	Hanzhong	Shaanxi	2020-2-9
Wenzhou	Zhejiang	2020-2-2	Wuxi	Jiangsu	2020-2-9
Huaian	Jiangsu	2020-2-3	Beijing	Beijing	2020-2-10
Hangzhou	Zhejiang	2020-2-4	Shanghai	Shanghai	2020-2-10
Ningbo	Zhejiang	2020-2-4	Inner Mongol	Inner Mongol	2020-2-12

Covid-19 [21]. We collect the latitude and longitude data of cities from the "Chinese Research Data Services Platform[5]", and use the data to calculate the distance of cities from Wuhan, by calculating the reciprocal of the calculated latitude and longitude distance and then determining the logarithm.

Urban Rail Transit

Rail transit is a main form transport in a modern city, carrying many people, including infected ones. As such, rail transit may exacerbate the spread of Covid-19 [22]. We use the dummy variable of whether the city has an open rail transit system to measure urt. If the city has an open rail transit system at the end of 2019, urt = 1; if not, urt = 0. The rail transit data are collected from "Annual Statistics and Analysis Reports of Urban Rail Transit".

Demographic and Economic Indicators

In addition to biological and epidemiological factors, many social and economic criteria also control the spread of an epidemic. It is confirmed that Covid-19 can spread from person to person so that cities with high population density are more likely to have early outbreaks and accelerate the spread of Covid-19 [23]. To capture this, population density is set as a population count per square kilometer. Annual data for 2018 are collected from the "China City Statistical Yearbook (2019)".

Economic development is measured using per capita GDP, and we hypothesize there is a negative correlation between the total number of Covid-19 cases and the per capita GDP. The level of medical service and public health services is higher in cities with better economic development, improving cities' response and epidemic control capabilities [24]. Cities with a higher level of economic development also tend to have healthier residents [25]. Covid-19 mainly affects vulnerable people with underlying health conditions [26]. Data reflecting 2018 per capita GDP are collected from the "China City Statistical Yearbook (2019)".

Descriptive Statistics

Table 2 reports the descriptive statistics of the study data. The average Covid-19 cases of each city is 3.4 over the period with a maximum number of 424. There is an average of 536.77 km between the study cities and Wuhan; 12.8% have opened urban rail transit. There are significant variations in size and economic development level across cities, with the average population density ranging from 563.97 to 10,625.37 individuals per square kilometer, and the per capita GDP ranged from 22,071 yuan to 179,513 yuan.

[5] China Research Data Service Platform, see https://www.cnrds.com/.

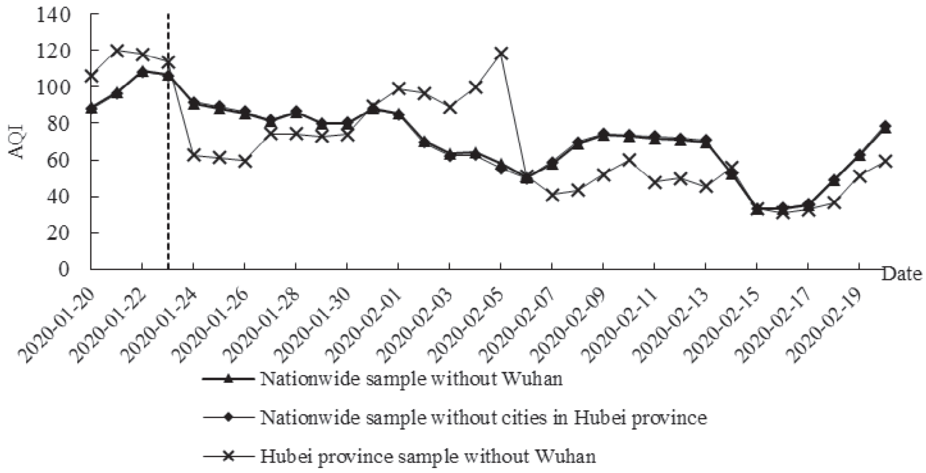

Fig. 4. Time trend of AQI.

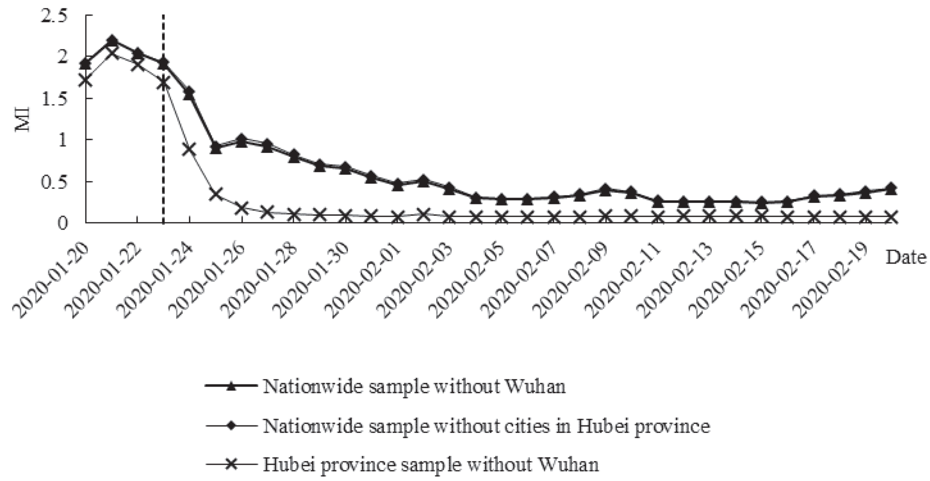

Fig. 5. Time trend of MI index.

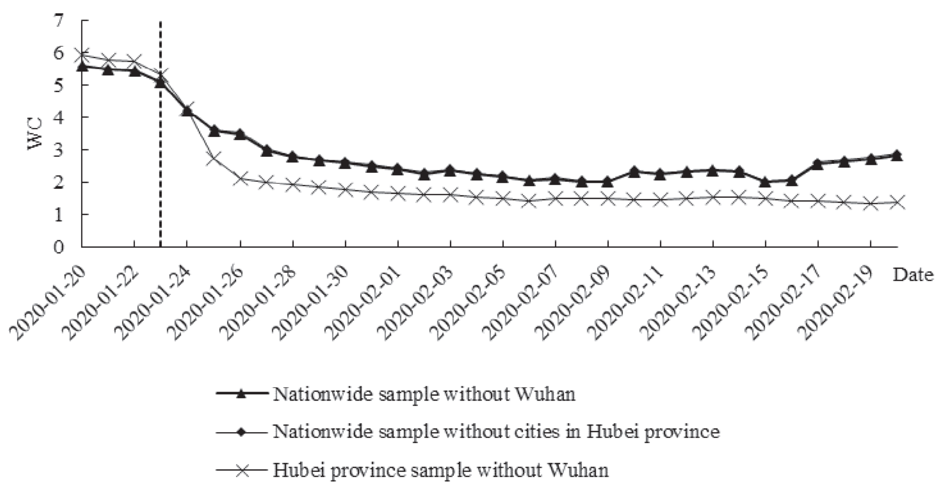

Fig. 6. Time trend of WC index.

Table 2. Descriptive statistics of variables.

Abbreviation of the variable	Observation	Mean	Std. Dev	Minimum	Maximum
INC	8224	3.400	15.343	0.000	424
CL	8224	0.463	0.499	0.000	1.000
ln*AQI*	8224	4.077	0.636	2.642	5.568
$\ln PM_{2.5}$	8224	3.660	0.774	1.618	5.365
$\ln PM_{10}$	8224	3.947	0.700	2.125	5.525
$\ln SO_2$	8224	2.196	0.677	0.829	3.996
$\ln NO_2$	8224	2.202	0.604	0.901	3.667
ln*CO*	8224	-0.193	0.431	-1.168	0.954
$\ln O_3$	8224	3.968	0.327	3.004	4.539
MI	8224	0.679	1.024	0.007	17.720
WC	8224	2.882	1.339	0.323	8.878
tem	8224	3.906	8.593	-18.700	21.200
pre	8224	1.743	5.439	0.000	33.900
humi	8224	4.974	1.764	2.100	9.700
ln*dis*	8224	-1.803	0.115	-1.992	-1.278
urt	8224	0.128	0.335	0.000	1.000
ln*rgdp*	8224	11.126	0.488	10.002	12.098
ln*pop*	8224	7.990	0.657	6.335	9.271

Each city experiences significant changes in air pollution during the study period. The average AQI index value is 58.97, with a minimum of 14.04 and a maximum of 261.91. For $PM_{2.5}$ concentrations, the mean value is 38.86 ug/m^3, with a minimum of 5.04 ug/m^3 and a maximum of 213.79 ug/m$_3$. For PM10 concentrations, the mean value is 51.78 ug/m^3, with a minimum of 8.37 ug/m^3 and a maximum of 250.89 ug/m^3. For SO_2 concentrations, the mean value is 8.98 ug/m^3, with a minimum of 2.29 ug/m3 and a maximum of 54.38 ug/m^3. For NO_2 concentrations, the mean value is 9.04 ug/m^3, with a minimum of 2.46 ug/m3 and a maximum of 39.13 ug/m^3. For CO concentrations, the mean value is 0.82 mg/m^3, with a minimum of 0.31 mg/m^3 and a maximum of 2.60 mg/m^3. For O_3 concentrations, the mean value is 52.88 ug/m^3, with a minimum of 20.17ug/m^3 and a maximum of 93.60 ug/m^3.

The mean daily move-in migration index is 0.68, with a maximum of 17.72; the daily mean within-city migration index is 2.88, with a maximum of 8.88.

The climate data show that the average daily temperature in the study cities for the study period is 3.9ºC, with a maximum of 21.2ºC. The mean 24 h accumulated precipitation is 1.7 millimeters, with a maximum value of 33.9 millimeters. The average relative humidity is 4.974, with a maximum of 9.700.

Empirical Results

Effect of Lockdown on Covid-19

The incubation period of Covid-19 means that any impact of a lockdown is hysteretic (characterized by a lag period). Lauer et al. (2020) [27] find that Covid-19 has a 5.1-day average incubation period. As such, we apply a 5-day lag period to the lockdown policy variables. Table 3 provides the initial DID estimation results from Eq. (5) with Model (1)-(2), providing the estimated impact of the lockdown on Covid-19 cases for the nationwide sample without Wuhan. Model (1) only includes the lockdown variable. Model (2) adds the interaction term between lockdown and air pollution, based on Model (1). To increase the robustness of the empirical results, we also estimated the regression results of DID under the PPML method in Model (3) and Model (4). The results show that the estimation results of the OLS method and the PPML method are consistent. However, PPML yields better estimation results compared to OLS based on the R^2 values. Given that, the subsequent analysis focus on the estimation results of PPML method.

The estimated lockdown coefficient in Model (3) indicates that the coefficient of CL×TIME is significantly negative, this indicates that the lockdown effectively reduces the spread of Covid-19, with a reduction of

Table 3. Estimation results of the DID model.

Variable	Nationwide sample without Wuhan				Nationwide sample without cities in Hubei province			
	Model (1) OLS	Model (2) OLS	Model (3) PPML	Model (4) PPML	Model (5) OLS	Model (6) OLS	Model (7) PPML	Model (8) PPML
CL×TIME	-0.500*** (-11.48)	-0.336*** (-7.32)	-0.311*** (-3.94)	-0.273*** (-3.53)	-0.600*** (-14.11)	-0.484*** (-10.25)	-1.058*** (-12.89)	-0.938*** (-10.12)
ln*AQI*		0.100** (5.28)		0.150** (3.47)		0.096*** (5.28)		0.128*** (3.59)
CL×TIME×ln*AQI*		0.294*** (7.66)		0.390*** (5.10)		0.168*** (3.91)		0.220*** (2.72)
tem	-0.004 (-0.94)	-0.011*** (-2.74)	0.008 (-0.78)	-0.001 (-0.07)	-0.007* (-1.62)	-0.012*** (-2.99)	-0.001 (-0.22)	-0.006 (-0.81)
pre	-0.011*** (-4.32)	-0.005* (-1.96)	-0.026*** (-4.38)	-0.016*** (-2.65)	-0.009*** (-3.77)	-0.005* (-1.75)	-0.025*** (-5.13)	-0.018** (-3.72)
humi	-0.002 (-0.16)	0.004 (0.38)	-0.063** (-2.06)	-0.076** (-2.67)	0.010 (0.98)	0.017 (1.64)	-0.033* (-1.68)	-0.025 (-1.27)
ln*dis*	2.352*** (5.93)	2.425*** (6.01)	1.913*** (5.01)	2.204*** (5.76)	2.978*** (4.98)	2.868*** (4.76)	6.291*** (7.68)	6.144*** (7.50)
urt	0.780*** (11.26)	0.794*** (11.32)	1.641*** (14.41)	1.672*** (15.80)	0.787*** (11.18)	0.793*** (11.19)	1.575*** (15.17)	1.580*** (15.18)
ln*rgdp*	-0.008 (-0.14)	-0.007 (-0.12)	-0.380*** (-3.30)	-0.383*** (-3.87)	0.018 (0.31)	0.020 (0.35)	-0.097 (-1.06)	-0.100 (-1.08)
ln*pop*	0.082** (2.05)	0.071* (1.77)	0.234*** (3.01)	0.213*** (2.77)	0.081* (1.94)	0.068 (1.63)	0.211*** (4.16)	0.183*** (3.58)
constant	5.442*** (5.33)	5.516*** (5.35)	8.237*** (4.80)	8.992*** (6.02)	6.266*** (4.82)	5.996*** (4.57)	11.380*** (7.74)	11.354*** (7.68)
Month fixed	Y	Y	Y	Y	Y	Y	Y	Y
Week fixed	Y	Y	Y	Y	Y	Y	Y	Y
Province fixed	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.072	0.109	0.654	0.674	0.105	0.122	0.336	0.340
N	3359	3359	6939	6939	3090	3090	6669	6669

Notes: *, **, *** represent significance levels of 10%, 5% and 1%, respectively. The z value of the coefficient is in parentheses.

31.1% for newly confirmed cases across the study cities (excluding Wuhan). This result validates Hypothesis 1 and is consistent with the result of Fang et al. (2020) [28].

An analysis of other control variables indicates that the coefficient of pre and humi are significantly negative. Increased precipitation levels make residents less willing to go outside and reduce social activities, also curbing the spread of Covid-19. High humidity conditions increase the size of aerosols and reduce the spread of viruses in the air. The regression coefficient of lndis is significantly positive, indicating that the spread of Covid-19 is more serious in cities closer to Wuhan. This finding is consistent with the results of Zhang et al. (2020) [16].

Having an open rail transit system significantly accelerates the spread of Covid-19, this finding is consistent with the results of Liu (2020) [22]. The coefficient of lnrgdp is significantly negative, which means that cities with higher economic levels have stronger ability to control the epidemic. This finding is consistent with the results of Pardhan and Drydakis (2021) [24]. The coefficient of lnpop is significantly positive, indicating that Covid-19 spread faster in cities with a higher population density. Finally, the regression results show that temperature has no significant effect on the spread of Covid-19.

The results of Model (4) in Table 3 show that the coefficient of CL×TIME×lnAQI is significantly positive. This indicates that the spread of Covid-19 is influenced by population movement, as well as the air pollution levels during lockdown. The lockdowns have a weaker effect on the spread of Covid-19 in cities with higher levels of air pollution. In other words, lockdowns have a stronger impact on pollution in cities with low air pollution levels. This may be because while lockdown blocks population movement between cities and within a city, some outdoor activities continue despite the lockdown. When the air pollution in the city is severe, these outdoor activities aggravate the spread of Covid-19.

To assess the robustness of the estimated results, we conduct a regression analysis on the nationwide sample

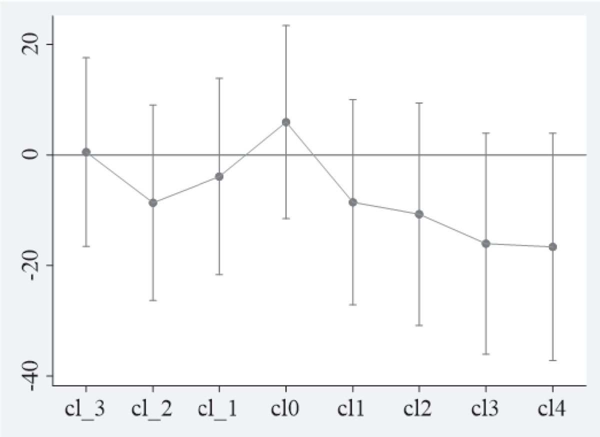

Fig. 7. Parallel trend test.
Notes: cl0 is the day when the lockdown starts to be implemented; cl_1, cl_2, and cl_3 represent the first day, the second day, and the third day before lockdown, respectively; cl1, cl2, cl3, and cl4 represent the first day, the second day, the third day and the fourth day after lockdown, respectively.

without cities in Hubei province (Models (5)-(8)). The coefficient of CL×TIME is significantly negative in Model (7), as is the coefficient of CL×TIME×lnAQI in Model (8). These results are consistent with the regression results of Model (3) and Model (4) respectively, and validate the robustness of the estimated results.

To ensure the robustness of the DID model results, we apply a parallel trend test (see Fig. 7). If the confirmed Covid-19 case counts are different between cities that do and do not implement lockdown measures (the treatment group and control group, respectively) before the lockdown began, then changes in Covid-19 risk are likely caused by the systematic differences between the cities, rather than the lockdown itself. In fact, we find no significant difference in the number of newly confirmed Covid-19 cases between cities in the treatment group and control group before the lockdown began. Hence, the lockdown does appear to be the factor leading to differences in the number of newly confirmed Covid-19 cases between cities in the treatment and control groups. In other words, the results of the DID estimation conform to the parallel trend assumption.

Effect of Air Pollution on Covid-19

Baseline Regression Results

Table 4 reports the results of the impact of air pollution on the spread of Covid-19. Model (1) and Model (2) represent the estimated results based on OLS and PPML, respectively. PPML yields better estimation results compared to OLS based on the R2 values. Given that, the subsequent analysis focus on the estimation results of Model (2). The coefficient of lnAQI is positively significant, indicating that air pollution accelerates the spread of Covid-19. This finding is consistent with the results of Wu et al. (2020) [8], Fareed et al. (2020) [9], Bashir et al. (2020) [10], and Cole et al. (2020b) [11]. The result validates Hypothesis 2. The additional increase of air pollutants in cities with already high air pollution levels increases the spread of Covid-19. Calculating the marginal effects indicates that an increase of one unit of AQI is associated with 1.723 more newly confirmed Covid-19 cases.

To ensure the stability of the results, we conduct a regression analysis on the nationwide sample without cities in Hubei province (Model (3) and Model (4)) and on the Hubei province sample without Wuhan (Model (5) and Model (6)). The estimated results of Model (4) and Model (6) indicate that the effects of air pollution on Covid-19 are also significantly positive, higher levels of air pollution accelerates the spread of Covid-19. This effect is the most significant in cities in Hubei province without including Wuhan.

Taking into account the endogenous problem of air pollution and Covid-19, we use instrumental variable (IV) to solve it. Hering and Poncet (2014) [29] use air velocity as an instrumental variable for air pollution, based on the fact that the higher the wind speed, the better the horizontal diffusion conditions of pollutants, and the higher the mixed layer, the better the vertical diffusion conditions of pollutants. We refer to this idea and use wind speed as an instrumental variable for air pollution, and use the two-stage least squares (2SLS) method to estimate the parameters. Regarding wind speed as a control variable, firstly, the higher the wind speed, the more conducive to the lateral diffusion of pollutants and meeting the correlation requirements of instrumental variables; secondly, as natural meteorological conditions, it satisfies the exogenous requirements. The 2SLS regression results in Table 5 indicate that F statistics in Model (1) and Model (2) are both significantly greater than 10, indicating no weak IV problem. This shows the effectiveness of IV, and the 2SLS regression results are consistent with the baseline regression in Table 4. In conclusion, these tests confirm that air pollution has a significant positive effect on Covid-19.

Panel Quantile Regression Results

Table 6 reports the panel quantile regression estimations based on Eq. (24). The estimation results of Model (1)-(5) correspond to the quantile values of 0.1, 0.3, 0.5, 0.7, and 0.9, respectively. The results show that the coefficients of lnAQI are all significantly positive, and continue to increase as the quantile value increases. The public health care system is overburdened in cities with a severe epidemic. And in these cities, the epidemic is more susceptible to air pollution, which leads to faster spread of Covid-19. Meanwhile, the effects of temperature and precipitation on Covid-19 are consistently negative across quantiles, and the effects of the distance from Wuhan and urban rail transit on Covid-19 are consistently positive. Higher temperatures

Table 4. Result of OLS and PPML estimator.

Variable	Nationwide sample without Wuhan		Nationwide sample without cities in Hubei province		Hubei province sample without Wuhan	
	Model (1) OLS	Model (2) PPML	Model (3) OLS	Model (4) PPML	Model (5) OLS	Model (6) PPML
ln*AQI*	0.202^{***} (7.14)	0.423^{***} (4.44)	0.175^{***} (6.35)	0.178^{***} (3.19)	0.684^{***} (4.53)	0.658^{***} (4.57)
tem	-0.023^{***} (-5.60)	-0.020^{*} (-1.78)	-0.027^{***} (-6.79)	-0.031^{***} (-4.63)	0.005 (0.17)	-0.011 (-0.44)
pre	-0.009^{***} (-3.41)	-0.026^{***} (-3.82)	-0.007^{***} (-2.95)	-0.022^{***} (-5.01)	-0.041^{**} (-2.68)	-0.039^{**} (-3.05)
humi	0.014 (1.31)	-0.036 (-1.24)	0.021^{**} (2.00)	-0.027 (-1.31)	-0.137^{**} (-2.27)	-0.097 (-1.62)
ln*dis*	2.343^{***} (6.09)	2.135^{***} (5.40)	2.692^{***} (4.58)	6.283^{***} (7.63)	1.651^{***} (3.43)	1.766^{***} (4.14)
urt	0.645^{***} (9.66)	1.580^{***} (14.45)	0.636^{***} (9.26)	1.423^{***} (13.71)	-	-
ln*rgdp*	-0.015 (-0.27)	-0.373^{***} (-3.44)	0.009 (0.16)	-0.090 (-0.97)	-0.809^{***} (-3.02)	-0.644^{***} (-3.58)
ln*pop*	0.064 (1.63)	0.221^{***} (2.78)	0.064 (1.55)	0.184^{***} (3.61)	-0.020 (-0.14)	0.235^{*} (1.89)
constant	4.592^{***} (4.59)	6.461^{***} (4.26)	5.059^{***} (3.92)	10.716^{***} (7.00)	12.369^{***} (3.32)	9.536^{***} (3.69)
Month fixed	Y	Y	Y	Y	Y	Y
Week fixed	Y	Y	Y	Y	Y	Y
Province fixed	Y	Y	Y	Y	N	N
R^2	0.037	0.629	0.042	0.293	0.137	0.370
N	3618	8224	3332	7904	286	320

Notes: Besides Wuhan, the other cities in Hubei province have not opened rail transit yet, thus this variable is removed from regression automatically. *, **, *** represent significance levels of 10%, 5% and 1%, respectively. The z value of the coefficient is in parentheses.

Table 5. 2SLS regression results.

Variable	Model (1) OLS	Model (2) PPML
ln*AQI*	0.485^{***} (3.69)	0.500^{*} (1.72)
tem	-0.037^{***} (-6.54)	-0.022 (-1.65)
pre	-0.001 (-0.31)	-0.017^{*} (-1.74)
humi	0.026^{**} (2.10)	-0.046 (-1.26)
Month fixed	Y	Y
Week fixed	Y	Y
Province fixed	Y	Y
F test	177.250^{***}	22.80^{***}
N	3612	8224

Notes: The results of Table 5 are based on the nationwide sample without Wuhan. *, **, *** represent significance levels of 10%, 5% and 1%, respectively. The z value of the coefficient is in parentheses. lndis, urt, lnrgdp, lnpop variables are removed from regression automatically.

harm the virus, and heavy precipitation leads to fewer outdoor activities, both help curb the spread of Covid-19. Finally, the epidemic is more severe in cities that are closer to Wuhan and have a better traffic system. Cities with more severe epidemics will cause these factors to have a more significant impact on the spread of Covid-19.

Heterogeneity Analysis

First, we analyze the heterogeneity of air pollutants. To further examine which kind of air pollutant influence the spread of Covid-19, the six air pollutants are used as key independent variables to generate estimates. Table 7 shows the results. The variable lnAIR incorporates $\ln PM_{2.5}$, lnPM10, $\ln SO_2$, $\ln NO_2$, lnCO, and $\ln O_3$. The results indicate that the coefficients of $\ln PM_{2.5}$, $\ln PM_{10}$, $\ln NO_2$, lnCO, and $\ln O_3$ are all significantly positive. That is, $PM_{2.5}$, PM_{10}, NO_2, CO, and O_3 all increase the spread of Covid-19. The effects of $PM_{2.5}$ and O_3 are more significant than other pollutants, suggesting that exposure to these may raise the risk of infection with Covid-19. This is because exposure to air pollutants

Table 6. Panel quantile regression results.

Variable	Model (1) Q.1	Model (2) Q.3	Model (3) Q.5	Model (4) Q.7	Model (5) Q.9
ln*AQI*	0.141*** (3.09)	0.157*** (4.53)	0.182*** (6.48)	0.203*** (5.58)	0.230*** (4.07)
tem	-0.011* (-1.80)	-0.013*** (-2.87)	-0.017*** (-4.50)	-0.020*** (-4.12)	-0.024*** (-3.17)
pre	-0.009** (-2.18)	-0.009*** (-2.92)	-0.010*** (-3.73)	-0.010*** (-2.95)	-0.010* (-1.96)
humi	-0.025 (-1.46)	-0.011 (-0.84)	0.010 (0.97)	0.029** (2.11)	0.052** (2.46)
ln*dis*	1.665*** (3.64)	1.930*** (5.54)	2.331*** (8.25)	2.684*** (7.33)	3.130*** (5.49)
urt	0.387*** (5.25)	0.487*** (8.63)	0.638*** (13.85)	0.772*** (13.00)	0.940*** (10.20)
ln*rgdp*	-0.037 (-0.63)	-0.035 (-0.80)	-0.033 (-0.93)	-0.031 (-0.68)	-0.029 (-0.41)
ln*pop*	0.053 (1.28)	0.057* (1.78)	0.062** (2.40)	0.066** (1.98)	0.072 (1.38)
Month fixed	Y	Y	Y	Y	Y
Week fixed	Y	Y	Y	Y	Y
Province fixed	Y	Y	Y	Y	Y
N	3618	3618	3618	3618	3618

Notes: The results of Table 6 are based on the nationwide sample without Wuhan. *, **, *** represent significance levels of 10%, 5% and 1%, respectively. The z value of the coefficient is in parentheses.

$PM_{2.5}$ and O_3 is related to human respiratory diseases. $PM_{2.5}$ may provide a good platform to carry the Covid-19 virus during atmospheric transportation [30]. And due to its small size, $PM_{2.5}$ easily penetrate into the lower respiratory tract and bring the virus directly into the alveolar and tracheobronchial regions [7, 31]. Ground-level O_3 can exacerbate chronic respiratory diseases and cause a short-term decline in lung function [32]. The coefficient of $\ln SO_2$ is not significant, indicating it do not significantly impact the spread of Covid-19.

Second, we analyze the heterogeneity of cities with different population sizes. Table 8 shows the results. The effects of air pollution on the spread of Covid-19 diminish as the population size increases. Air pollution levels has a more significant effect on the spread of Covid-19 in small and medium-sized cities compared to big cities. This is because the urban governance capability of small and medium-sized cities is generally less adequate than larger cities; the management capability of local governments and the response capability of residents are relatively weak; and people in these cities are more likely to be exposed to outdoor activities. Big cities have a larger population and generally more severe air pollution, however, they also generally have a stronger management capability, and local governments and resident in big cities are more sensitive to Covid-19. Residents in big cities reduce outdoor activities during lockdown, and population movement within cities is strictly restricted. This lowers the probability of exposure to outdoor activities. Thus, the significance of air pollution on the spread of Covid-19 is lower in big cities than in small and medium-sized cities.

Mechanism Analysis of Lockdown on Covid-19

We further explore the mechanism by which the lockdown impacts Covid-19, to examine whether lockdown can curb the spread of Covid-19 by reducing air pollution and population movement between and within cities. As described above, lnAQI, MI, and WC as the mediating variables. Due to the incubation period of Covid-19, floating populations may not immediately show symptoms after arriving in a city, and there is a time interval between isolation, nucleic acid testing, and confirmation. Thus, there is a lag in the effect of population movement on Covid-19. We process both MI and WC with a lag time of 5 days to obtain variables MI_5 and WC_5. In other words, population migration data on 15 January 2020 correspond to confirmed cases on 20 January 2020. The same lag is applied throughout the study period.

We follow the conditional verification step settings used by Baron and Kenny (1986) [33] as follows:

First, we set CL×TIME as an independent variable and lnAQI, MI, and WC as dependent variables. We establish three econometric models for estimation. Significant estimation coefficients of CL×TIME in the

Table 7. Pollutant heterogeneity analysis results.

Variable	Model (1) $PM_{2.5}$	Model (2) PM_{10}	Model (3) SO_2	Model (4) NO_2	Model (5) CO	Model (6) O_3
ln*AIR*	0.403*** (5.14)	0.295*** (3.28)	-0.003 (-0.04)	0.237*** (2.81)	0.181* (1.78)	0.814*** (5.52)
tem	-0.023** (-2.05)	-0.017 (-1.54)	-0.011 (-1.12)	-0.005 (-0.42)	-0.015 (-1.39)	-0.006 (-0.63)
pre	-0.023*** (-3.52)	-0.028*** (-4.08)	-0.034*** (-5.16)	-0.037*** (-5.50)	-0.033*** (-4.93)	-0.037*** (-5.66)
humi	-0.027 (-0.90)	-0.045 (-1.55)	-0.046 (-1.54)	-0.051* (-1.73)	-0.036 (-1.18)	-0.145*** (-4.51)
ln*dis*	2.149*** (5.50)	2.026*** (5.20)	1.959*** (5.00)	2.143*** (5.80)	1.901*** (4.93)	1.998*** (5.03)
urt	1.575*** (14.50)	1.608*** (14.70)	1.570*** (13.87)	1.535*** (13.66)	1.581*** (13.78)	1.528*** (13.77)
ln*rgdp*	-0.370*** (-3.45)	-0.386*** (-3.41)	-0.368*** (-3.14)	-0.239** (-1.87)	-0.377*** (-3.23)	-0.320*** (-2.80)
ln*pop*	0.226*** (2.87)	0.200** (2.47)	0.240*** (3.04)	0.271*** (3.42)	0.240*** (3.05)	0.211*** (2.61)
constant	6.800*** (4.35)	7.370*** (4.54)	7.891*** (4.54)	5.907*** (2.98)	7.895*** (4.57)	4.807*** (2.92)
Month fixed	Y	Y	Y	Y	Y	Y
Week fixed	Y	Y	Y	Y	Y	Y
Province fixed	Y	Y	Y	Y	Y	Y
R^2	0.632	0.626	0.622	0.624	0.622	0.630
N	8224	8224	8224	8224	8224	8224

Notes: The results of Table 7 are based on PPML model and nationwide sample without Wuhan. AIR in model (1)-(6) represents $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO and O_3 respectively. *, **, *** represent significance levels of 10%, 5% and 1%, respectively. The z value of the coefficient is in parentheses.

three models indicate that lockdown does impact air pollution and population movement. The first step is to test whether CL×TIME affects lnAQI, MI, and WC.

$$\ln AQI_{it} = \alpha_0 + \alpha_1 CL_{it} \times TIME_{it} + \lambda_j \sum_{j=1}^{n} Z_{jit} + v_i + u_t + \varepsilon_{it} \tag{7}$$

$$MI_{it} = \alpha_0 + \alpha_1 CL_{it} \times TIME_{it} + \lambda_j \sum_{j=1}^{n} Z_{jit} + v_i + u_t + \varepsilon_{it} \tag{8}$$

$$WC_{it} = \alpha_0 + \alpha_1 CL_{it} \times TIME_{it} + \lambda_j \sum_{j=1}^{n} Z_{jit} + v_i + u_t + \varepsilon_{it} \tag{9}$$

where the explanation of the other variables is consistent with Eq. (5) and Eq. (6).

Second, we further set lnAQI, MI, and WC as independent variables, and INC as a dependent variable for regression analysis. Significant coefficients of lnAQI, MI, and WC indicate that air pollution and population movement affect the spread of Covid-19. In other words, the second step tests whether lnAQI, MI, and WC affect INC.

$$INC_{it} = \alpha_0 + \alpha_1 \ln AQI_{it} + \alpha_2 MI_{it} + \alpha_3 WC_{it} + \lambda_j \sum_{j=1}^{n} Z_{jit} + v_i + u_t + \varepsilon_{it} \tag{10}$$

Third, if the results of the above steps are both true, we further use CL×TIME, lnAQI, MI, and WC as independent variables at the same time. The variable INC serves as the dependent variable for regression analysis. If there is a decrease or a significant decrease in the coefficient of CL×TIME, it indicates that the effect of CL×TIME on INC is partly or entirely from the mediation effects of lnAQI, MI, and WC. That is, the third step tests whether CL×TIME, lnAQI, MI, and WC affect INC at the same time. The test formula used is as follows:

$$INC_{it} = \alpha_0 + \alpha_1 CL_{it} \times TIME_{it} + \alpha_2 \ln AQI_{it} + \alpha_3 MI_{it} + \alpha_4 WC_{it} + \lambda_j \sum_{j=1}^{n} Z_{jit} + v_i + u_t + \varepsilon_{it} \tag{11}$$

Table 8. Heterogeneity analysis results of different city sizes.

Variable	Model (1) Small-sized City (Population<0.5Million)	Model (2) Median-sized City (0.5Million≤Population <1Million)	Model (3) Big City (Population≥1Million)
ln*AQI*	0.988** (2.52)	0.785*** (4.90)	0.150 (1.63)
tem	0.013 (0.29)	-0.047* (-1.80)	-0.017* (-1.66)
pre	-0.067 (-1.35)	-0.019* (-1.77)	-0.029*** (-3.95)
humi	-0.112 (-0.96)	-0.103* (-1.77)	-0.030 (-0.94)
ln*dis*	-7.343 (-0.46)	2.975*** (2.94)	1.236*** (2.80)
urt	-	-	1.237*** (11.20)
ln*rgdp*	-2.018** (-2.37)	-0.300 (-1.57)	-0.144 (-1.24)
ln*pop*	0.076 (0.07)	0.116 (0.89)	0.193* (1.85)
constant	12.319 (0.50)	7.481*** (3.92)	3.466* (1.83)
Month fixed	Y	Y	Y
Week fixed	Y	Y	Y
Province fixed	Y	Y	Y
R^2	0.854	0.756	0.483
N	736	2560	4896

Notes: The results of Table 8 are based on the PPLM model and nationwide sample without Wuhan. The division of city size is based on "Notice on the adjustment of the standards for the division of city size (2014)". Under the new standards, cities with a population under 500,000 are defined as "small-sized cities", cities with a population between 500,000 and 1,000,000 are defined as "median-sized cities", cities with a population of more than 1,000,000 are defined as "big cities". As cities in Model (1) and Model (2) do not open rail transit lines, thus, urt is removed from regression. *, **, *** represent significance levels of 10%, 5% and 1%, respectively. The z value of the coefficient is in parentheses.

Table 9 shows the results of mediating mechanism between lockdown and the spread of Covid-19. Model (1)-(3) represent the results of the first step. The coefficients of CL×TIME are all significantly negative, indicating that lockdown reduces air pollution by 10.0%, and reduces the daily move-in migration index and daily within-city migration index by 23.9% and 18.8%, respectively.

Model (4) is the result of the second step. The coefficients of lnAQI, MI, and WC are all significantly positive, indicating that air pollution, daily move-in migration, and daily within-city migration all exacerbate the spread of Covid-19. In other words, decreasing the air pollution and the daily move-in and daily within-city migration help reduce the spread of Covid-19.

Model (5) is the result of the third step. After we introduce variables, including CL×TIME, lnAQI, MI, and WC into the model at the same time, the coefficient of CL×TIME becomes insignificant (in comparison with Model (6)). This indicates that that lockdown curbs the spread of Covid-19 by reducing air pollution, and decreasing daily move-in and daily within-city migration.

Discussion and Conclusion

The outbreak of Covid-19 at the end of 2019 became a black swan event, significantly threatening human health, economic development, and social stability. Epidemic prevention measures, such as lockdown, have also plunged many small and medium-sized enterprises into crisis [34]. Epidemic outbreaks, such as Covid-19, relate closely to our ecosystem and human activities. The spread of Covid-19 is also influenced by many factors involving the economy and public policy. China has a vast territory, many cities with diverse features, intricate transportation networks, and large-scale population movements. As such, the spread of Covid-19 in China exhibits both temporal and spatial characteristics. The central and local governments take active response measures, keeping the situation stable

Table 9. Estimation result of the mechanism analysis.

Variable	Model (1) lnAQI	Model (2) MI	Model (3) WC	Model (4) INC	Model (5) INC	Model (6) INC
CL×TIME	-0.100*** (-6.23)	-0.239*** (-9.41)	-0.188*** (-5.77)		0.032 (0.75)	-0.143*** (-3.51)
ln*AQI*				0.074** (2.55)	0.074** (2.54)	
*MI*_5				0.156*** (11.76)	0.156*** (11.79)	
*WC*_5				0.044*** (3.23)	0.048*** (3.31)	
tem	0.019*** (13.32)	0.011*** (4.75)	0.027*** (9.44)	-0.010*** (-2.59)	-0.010*** (-2.60)	-0.014*** (-3.41)
pre	-0.029*** (-27.20)	-0.004** (-2.14)	-0.004 (-1.63)	-0.009*** (-3.30)	-0.008*** (-3.29)	-0.014*** (-5.57)
humi	-0.060*** (-16.19)	-0.028** (-4.78)	-0.029*** (-3.84)	0.004 (0.34)	0.004 (0.35)	0.003 (0.33)
ln*dis*	0.360*** (3.10)	0.814*** (4.42)	-0.381 (-1.62)	2.206*** (9.77)	2.208*** (9.77)	2.352*** (10.10)
urt	-0.002 (-0.09)	1.206*** (39.02)	-0.728*** (-18.43)	0.435*** (8.73)	0.428*** (8.45)	0.677*** (14.89)
ln*rgdp*	0.011 (0.79)	0.057** (2.57)	-0.361*** (-12.67)	0.004 (0.11)	0.006 (0.15)	-0.032 (-0.86)
ln*pop*	0.057*** (5.78)	0.110** (7.06)	-0.007 (-0.35)	0.018 (0.65)	0.017 (0.64)	0.073*** (2.64)
constant	5.071*** (17.97)	3.637*** (8.13)	7.444*** (13.02)	3.963*** (6.12)	3.930*** (6.06)	5.719*** (8.86)
Month fixed	Y	Y	Y	Y	Y	Y
Week fixed	Y	Y	Y	Y	Y	Y
Province fixed	Y	Y	Y	Y	Y	Y
R^2	0.231	0.405	0.460	0.178	0.178	0.122
N	8224	8224	8224	3618	3618	3618

Notes: The results of Table 9 are based on the nationwide sample without Wuhan. *, **, *** represent significance levels of 10%, 5% and 1%, respectively. The z value of the coefficient is in parentheses.

and controllable in a short amount of time. In this context, a scientific evaluation and summary of the factors influencing Covid-19 and the effects of implementing lockdown can provide an important reference for future epidemic prevention and urban governance. We discuss the correlation between lockdown policy, air pollution and the spread of Covid-19. The main mechanism of the lockdown policy affecting the spread of Covid-19 was discussed.

Actually, the existing literature has expanded on the relationship between lockdown and the transmission of Covid-19, which can be broadly classified into four categories.

The first is to give a qualitative judgment by directly comparing the case data before and after lockdown. Typical examples such as Haider et al. (2020) [35] summarize the design, timing and specific measures of lockdown measures in nine countries in sub-Saharan Africa. By comparing the case data before and after the implementation of the lockdown policy, it is pointed out that the lockdown policy actually has a limited role in curbing the spread of Covid-19 in these countries due to limited average living space and shared health facilities.

The second is to simulate the impact of urban lockdowns by using mathematical models (e.g. SIR class models) and relying on existing data to estimate model parameters. For example, Alrashed et al. (2020) [36] and Fu et al. (2021) [37] set the relevant parameters of the extended SIR model according to the spread of Covid-19 data in Saudi Arabia and the UK respectively, and simulated the evolution of the spread of Covid-19 after the implementation of the lockdown policy, which proved the important role of lockdown in inhibiting the spread of Covid-19.

The third is the conventional linear regression model. This type of model is mainly used to analyze the impact of certain social and economic factors on the spread of Covid-19. The evaluation of the impact of lockdown on the spread of Covid-19 is mainly done by comparing the model structure and estimator estimated at different time points. Kharroubi and Saleh (2020) [38] used a Poisson regression model to estimate the changes in new cases before and after the implementation of the lockdown policy based on Lebanon's new case data. Bourdin et al. (2020) [39] established the spatial autoregressive model and used the cross-sectional data at three time points after the implementation of the lockdown policy for regression. It was found that after the implementation of the lockdown policy, the spatial autoregressive coefficient gradually decreased, which proved that the lockdown policy did slow down the spread of Covid-19.

The fourth is the policy evaluation linear regression model (e.g., DID class model). Its basic logic is to use the time inconsistency of each city's implementation of the closure policy and divide each city into the control group and the treatment group before and after the policy treatment through the setting of dummy variables. Construct a quasi-natural experimental model to judge the quality of a policy. For example, Fang et al. (2020) [28] used the DID method to estimate the impact of the lockdown policy on three types of population movements: between cities, within the city, and out of the city. They find that the lockdown reduced the three types of population movements in Wuhan by more than 50%.

In summary, although the analysis method are different, the first and third types of literature are more inclined toward comparative research. Both of them can validate the importance of the lockdown policy, but they cannot quantitatively give the specific impact intensity of the lockdown policy. The core purpose of the second type of literature is to predict the impact of policies such as lockdown, which helps to form the intuition of policy effects but is not suitable for ex-post evaluation of policy because its evaluation uses simulation rather than real data after all. The fourth type of literature is most suitable for evaluating specific policies. However, such a framework is more commonly used in analyzing the changes in the associated elements (rather than Covid-19 itself) that the lockdown may lead to. For example, Fang et al. (2020) [28] and He et al. (2020) [4] discussed the effects of lockdown on population mobility and air pollution, respectively. One possible reason for the limited use of the framework (on the relationship between lockdown and Covid-19) is that there may be a large number of zero values in the dependent variables (i.e., Covid-19 transmission indicators), which leads to a biased estimation problem. Zhang et al. (2020) [16] indicates that PPML estimator should be used to solve such problems.

This paper explores the impact of the lockdown on Covid-19 from the perspective of its impact on air pollution and population mobility. First, we establish an extended SIR model that incorporates the effects of lockdown and air pollution to help us establish research intuition, analyze the theoretical mechanism of how lockdown affects Covid-19, and propose hypotheses. Secondly, we use the DID model to empirically estimate the impact of lockdown on the spread of Covid-19. Third, we establish a linear regression model to empirically estimate the impact of air pollution on Covid-19. We further used the panel quantile model and grouping regression to analyze the heterogeneity of the impact of air pollution on Covid-19 from the perspective of different Covid-19 intensities, different air pollutants and different city sizes. After verifying the impact of air pollution on Covid-19, we find that air pollution is likely to also be an important mechanism for the lockdown to affect the spread of Covid-19. Therefore, we discuss it as a mechanism variable at the same time as population mobility and analyze how the lockdown affects the spread of Covid-19 by changing population mobility and air pollution.

Similar to most of the previous literature, the results of this study demonstrate that lockdown could effectively suppress the spread of Covid-19 while air pollution would accelerate the spread of Covid-19. Specifically, based on the regression results, this paper finds that the implementation of the lockdown policy in Wuhan and the whole country has reduced the number of new confirmed cases by an average of 31.1% (excluding Wuhan), while the air quality index increases by 1.723 new confirmed cases per unit.

Furthermore, this research makes the following findings through mechanism verification and heterogeneity analysis.

First of all, we find that in addition to population mobility, air pollution is also an important mechanism variable for blocking the spread of Covid-19, that is, Covid-19 can be suppressed by reducing air pollution (Table 9), which complements the conclusions of Fang et al. (2020) [28] and Zhu et al. (2020) [40]. Moreover, according to Table 3, when air pollution levels are high, the ability of the lockdown to suppress the spread of Covid-19 would be greatly weakened. On the whole, if the air pollution in the city is caused by the regular production and operation activities within the city (that is, they can be suspended after the lockdown), the ability of the lockdown to suppress the spread of Covid-19 is less affected by air pollution. However, if the air pollution in the city is exogenous or generated by the basic functioning of the city, such as atmospheric transmission, fossil energy heating, etc., the effect of lockdown may be relatively poor.

Second, considering that the relationship between multiple pollutants and Covid-19 is still controversial [41], we verify the influence of $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO and O_3 on the spread of Covid-19. We find that, all air pollutants accelerate the spread of Covid-19 except SO_2, which is basically consistent with the results of Zhu et al. (2020) [40]. But our results imply $PM_{2.5}$ and O_3 have greater effects than other pollutants.

Third, we also find that the impact of air pollution on Covid-19 transmission decreases with population size, and its impact is more significant in small and medium-sized cities than in large cities (Table 8). At the same time, the conclusion of this paper shows that population density has an important impact on the spread of Covid-19 (Table 4), which is similar with Bourdin et al. (2020) [39]. Moreover, our regression results suggest that the larger the population size, the greater the impact of population density on Covid-19 transmission (Table 8). In our opinion, the possible reason is that although cities with different population sizes may have similar population density, the public facilities of cities with larger population sizes serve more people, which leads to close social distance and an increased risk of infection [42]; accordingly, the role of population density is more significant. For small and medium-sized cities, with the reduction of close-contact scenes, the role of air pollutants as virus transmission media would be relatively more important.

Fourth, according to the results of panel quantile regression, we also find that the impact of air pollution on Covid-19 transmission is related to the severity of Covid-19 itself. The more serious the epidemic, the stronger air pollution's accelerating effect on transmission. The reason could be that more sources of infection exist in severe epidemics, the air pollutants are more likely to "load the virus" during the flow process, causing the virus to spread even more quickly. Corresponding with our extended SIR model or other comparable models [36, 37] in existing literature, more infected cases and more serious air pollution indicate that the actual contact rate value is higher, meaning that there is a greater risk of infection in the community.

The analysis above highlights three policy recommendations.

In the first place, the impacts of the lockdown might be minimal in cities with significant levels of air pollution. Spraying disinfectants on a large scale is a reasonably practical response to reduce virus survival among air pollutants if a direct reduction in air pollution level is hard to achieve by mere lockdown policy.

In another, between cities with large populations and cities with small to medium-sized populations, there are certain distinctions in the prevention and control priorities. The former primarily emphasizes scenarios that involve reducing population density and introducing measures like online work and staggered work to disperse population mobility, and the necessity of lockdown is relatively high; however, cities with small and medium-sized populations have fewer close-contact scenes, and the government can focus more on minimizing air pollution or reducing virus survival among air pollutants. It can selectively impose restrictions in particular locations with heavy foot traffic as an alternative to mass lockdown.

What is more, monitoring air pollution should be an important aspect of prevention and control work in cities with more infected people and new illnesses. Residents' flow should be strictly restricted in regions with severe pollution. Air filtering facilities or daily disinfection should be provided for specific locations where the human mobility is difficult to control.

This paper tried to provide supporting evidence on the impact of city lockdown and air pollution on the spread of Covid-19 in China. However, there are many complex unknown factors that often hinder a definitive assessment of the role of city lockdown and air pollution in the spread of Covid-19. For example, staying indoors for a long time and reducing interpersonal interaction can lead to anxiety behaviors and stress disorders, as well as increase the risk of indoor air pollution [43]. Due to the availability of indoor air pollution data, we only consider the impact of outdoor air pollution on the spread of Covid-19. The AQI and the 6 types of air pollutants used in this paper measure outdoor air pollution levels. In future research, if we can obtain indoor pollution levels, we can consider the impact of outdoor air pollution and indoor air pollution on the spread of Covid-19 at the same time. This will make our research more comprehensive.

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Conflict of Interest

The authors declare no conflict of interest.

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Appendix

Theoretical Model

We apply the extended SIR model used by Robert (2020) and Chudik et al. (2020) to contain the variable of death and to account for the effect of air pollution and lockdown on Covid-19 [1, 2]. The extended SIR model is written as:[1]

$$P = S_t + I_t + R_t + D_t \tag{1}$$

where P denotes the total population size of a region. The model assumes P is a constant value and consists of four different types of people: S, I, R, and D; S_t refers to people who have not yet been infected with Covid-19 during the t period. Because of the risk of infection, they are also called susceptible people; It refers to people who have been infected with Covid-19 during the t period; R_t refers to people who have recovered; D_t denotes people who have died. We assume that people who have recovered from Covid-19 would be no longer susceptible.

To explore the impact of lockdown on the epidemic, we apply the method used by Chudik et al. (2020) [2]. The P in Eq. (1) is divided into two groups: Pl is the fraction of the population that is healthy and has been isolated; P_e is the fraction of the population exposed to Covid-19. We assume that the risk of getting infected with Covid-19 is low for people who have been isolated. Therefore, the model associated with the lockdown is written as:

$$P_e = \delta P = S_t + I_t + R_t + D_t \tag{2}$$

where δ is the proportion of P_e to P. The expression 1-δ measures the level of lockdown enforcement. Cities with a higher value of 1-δ implement stricter lockdown measures. A value of δ = 1 indicates the city has no lockdown.

We further transform the expanded SIR model into a set of differential equations. In contrast to previous studies, we consider the effect of air pollution on Covid-19. These equations are as follows:

$$S_{t+1} - S_t = -a\beta \frac{S_t}{P_e} I_t \tag{3}$$

$$I_{t+1} - I_t = a\beta \frac{S_t}{P_e} I_t - \left(\frac{1}{a}\gamma_r + a\gamma_d\right) I_t \tag{4}$$

$$R_{t+1} - R_t = \frac{1}{a}\gamma_r I_t \tag{5}$$

$$D_{t+1} - D_t = a\gamma_r I_t \tag{6}$$

where β is the contact rate of Covid-19, which depends on the biological nature of the Covid-19 virus and which we assume does not change with time or place; γr and γd are the recovery rate and the death rate, respectively; they are treated as constants, although they may change due to difference in medical response capabilities across cities; a is the impact coefficient of air pollution. Air pollution can accelerate the spread of the epidemic, decrease the rate of recovery, and increase the death rate [4-7]. Thus, we consider aβ, γ_r/a, and aγd to be the actual contact rate, the actual recovery rate, and the actual death rate of Covid-19, respectively, under the influence of air pollution. We set a>1; a higher value of a is associated with more severe air pollution. We assume that susceptible people will get infected with Covid-19 from infected people at time t in this model, leading to a secondary infection of aβst. The time distribution of It largely depends on the basic reproduction number, namely the number of secondary infections (R0) caused by one infected person, R0 = aβ/(γ_r/a + aγd).

We divide both sides of the above equations by P, yielding the following equations:

$$s_{t+1} - s_t = -\frac{a\beta}{\delta} s_t i_t \tag{7}$$

$$i_{t+1} - i_t = \frac{a\beta}{\delta} s_t i_t - \left(\frac{1}{a}\gamma_r + a\gamma_d\right) i_t \tag{8}$$

$$\delta = s_t + i_t + r_t + d_t \tag{9}$$

where $s_t = S_t/P$, $i_t = I_t/P$, $r_t = R_t/P$, and $d_t = D_t/P$; aβ/δ is the effective actual contact rate, and ν = aβ/δ. When δ = 1, it means a lockdown has not been implemented and everyone is randomly exposed to Covid-19. In this case, the effective actual contact rate is consistent with the actual contact rate, ν = aβ.

We assume that the spread of Covid-19 starts with a non-zero initial value: It>0, St>0. Eq. (7) and Eq. (8) are solved by iterating forward a selected non-zero initial value. We assume that r1 = d1 = 0; the value of i1 is very small at the beginning of the Covid-19 outbreak; thus: s1 = δ-i1. Hence, we start with i1 (i1>0) and s1 to iterate Eq. (8) forward, yielding the following equations:

[1] The basic SIR model for simulating the spread of infectious diseases was first developed by Kermack and McKendrick (1927) [3].

$$i_{t+1} = (\prod_{\tau=1}^{t} \lambda_\tau) i_1 \tag{10}$$

$$\lambda_\tau = 1 + (\frac{1}{a}\gamma_r + a\gamma_d)(\frac{R_0}{\delta} s_\tau - 1) \tag{11}$$

Initially, there are few Covid-19 cases: sτ is close to the value of δ, and λτ>1. In this situation, if R0>1, the number of confirmed cases is expected to increase exponentially. However, as the pandemic develops, the recovered and dead people are gradually removed; they no longer become infected. Then, there is a certain point in time t = t*. When τ> t*, sτ begins to decrease, λτ<1. In this case, the value in the parentheses of Eq. (10) approaches 0 and is expressed as:

$$\lim_{t\to\infty} (\prod_{\tau=1}^{t} \lambda_\tau) = 0 \tag{12}$$

Hence, we have:

$$\lim_{t\to\infty}(i_t) = i^* = 0, \quad \lim_{t\to\infty}(i_{t+1}/i_t) = 1 \tag{13}$$

$$\lim_{t\to\infty}(s_t) = s^* = \delta(\frac{1}{a}\gamma_r + a\gamma_d)/(a\beta) \tag{14}$$

Eq. (13) indicates that i* = 0. Hence, δ = s*+r*+d*. We use c* to measure the proportion of infected cases to the total population, yielding:

$$c^* = r^* + d^* = \delta - s^* = \delta - \delta(\frac{1}{a}\gamma_r + a\gamma_d)/(a\beta) \tag{15}$$

We focus on the variation of a and δ in the Covid-19 curve. To get the functions related to a, δ and it, we need to eliminate st in Eq. (14). Based on Eq. (7) and Eq. (8), we have:

$$\frac{s_{t+1}}{s_t} = 1 - \frac{a\beta}{\delta} i_t \tag{16}$$

$$\frac{i_{t+1}}{i_t} = 1 + \frac{a\beta}{\delta} s_t - (\frac{1}{a}\gamma_r + a\gamma_d) \tag{17}$$

Because aβ/δ = ν>0, according to Eqs (16-17), we generate Eqs (18-19) as follows:

$$s_t = (\frac{i_{t+1}}{i_t} - 1 + \frac{1}{a}\gamma_r + a\gamma_d)\frac{\delta}{a\beta} \tag{18}$$

$$\frac{s_{t+1}}{s_t} = \frac{(\frac{i_{t+2}}{i_{t+1}} - 1 + \frac{1}{a}\gamma_r + a\gamma_d)\frac{\delta}{a\beta}}{(\frac{i_{t+1}}{i_t} - 1 + \frac{1}{a}\gamma_r + a\gamma_d)\frac{\delta}{a\beta}} = 1 - \frac{a\beta}{\delta} i_t \tag{19}$$

Finally, the second-order nonlinear difference equation of it is expressed as:

$$i_{t+1} = \frac{i_t^2}{i_{t-1}} + \frac{a\beta}{\delta}[i_t i_{t-1}(1 - \frac{\gamma_r}{a} - a\gamma_d) - i_t^2] \tag{20}$$

We assume the initial value of i_1 and i_2 are functions of δ in Eq. (20). This yields:

$$i_1(\delta) = \frac{\delta}{1000}, \quad i_2(\delta) = [1 + \frac{a\beta}{\delta}(\delta - \frac{\delta}{1000}) - (\frac{\gamma_r}{a} + a\gamma_d)]\frac{\delta}{1000} \tag{21}$$

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