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The impact of lockdown on air pollution: Evidence from an instrument

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ABSTRACT

This paper studies the impact of lockdown measures in response to the outbreak of COVID-19 on a prefecture's air pollution in China. To avoid potential endogenous problems, we exploit the bilateral population flow from the Baidu Migration Index to predict prefectures' probability to undertake lockdown measures. Our results using difference-in-differences with the instrumental variable show that a prefecture's lockdown measures significantly reduce its air quality index (AQI) by around 35%, and yet the result for difference-in-differences with OLS is only around 11%. We also find that a prefecture under lockdown reduces its PM_{10} and $PM_{2.5}$ by around 25% and 35% respectively, and the results of diff-in-diff with OLS are only around 11% and 12%. The sharp difference between these two approaches seems to imply that there is a strong heterogeneity in lockdown stringency across prefectures.

1. Introduction

The outbreak of the highly infectious coronavirus COVID-19 has had a substantial impact on human health. In order to curb its spread, many local governments in China undertook lockdown measures which substantially limited the mobility of the population and the operation of factories and other businesses. This study contributes to our understanding of the impact of local Chinese prefectures' lockdown measures on their air quality, and explores the potential channel in air quality changes. To do so, we exploit the policy responses of the local governments in the face of the COVID-19 outbreak as a quasi-natural experiment. China provides a good case study because COVID-19 first broke out in China near the end of 2019, and more than one third of Chinese prefectures undertook massive, unprecedented lockdown measures to curb the spread of the disease. Moreover, industrial development in China is associated with a substantial increase in air pollution, which poses a threat to public health. The problem of air pollution in China receives considerable attention in academia (Chen, Jin, Kumar, & Shi, 2013; Greenstone, He, Jia, & Liu, 2020; He, Fan, & Zhou, 2016). To conduct our analysis, we employ a difference-in-differences (henceforth diff-in-diff) identification strategy to estimate the effect of a prefecture's lockdown measures on its air quality. Then, we use the rich information of the lockdown documents from local office to discuss the heterogeneity in the effects of lockdown measures. Finally, by collecting the most recent air quality data from monitoring Stations, we are able to check the long-term effect of lockdown measures.

Due to our high frequency (daily) data, we can compare the average change of a prefecture's air quality precisely before and after a

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prefecture's lockdown. The key challenge to our identification strategy is that both a prefecture's decision to undertake and the timing of undertaking a lockdown might not be random. We consider the political concerns of the local government. There are two potential concerns that might affect a local political leader's decision to implement lockdown measures. The first one is economic. A lockdown measure implies shutting down restaurants, hotels, and factories, which slows the growth of the local economy considerably. Given that a politician's promotion opportunity is closely linked with economic growth (Jia, Kudamatsu, & Seim, 2015; Li & Zhou, 2005), he or she might be reluctant to enact such measures until the situation is quite bad. The second concern is that a local politician could be replaced if the spread of COVID-19 gets out of control.[1]

To address this issue, we construct a prefecture's time-varying risk of COVID-19 outbreak, conditional on the average inflow of population from epidemic areas (other prefectures). This measure can be used to predict a prefecture's decision regarding lockdown measures. Our identification strategy relies on the fact that if a prefecture receives a significant inflow of population from an epidemic area, this prefecture might face a high risk of COVID-19 outbreak and should undertake lockdown measures (Fang, Wang, & Yang, 2020).[2] To construct our instrument, we use a prefecture's population inflow from another prefecture p', to capture the relative importance of population flow from p' to p between January 1st and January 9th.[3] Before the outbreak of COVID-19, we believe the local governments had no incentives to manipulate this population flow out of the COVID-19 concerns. Therefore, this population flow could be treated as exogenous. To construct the time-varying aspect of a prefecture's COVID-19 risk, we use a time-varying dummy to indicate whether prefecture p' had more than a certain number of confirmed cases $\overline{C}$ at time t. The combination of these two variables allows us to predict whether a prefecture received a high inflow of population from a COVID-19 epidemic area, and whether this prefecture should have undertaken a lockdown.

We first use a diff-in-diff identification strategy to estimate the impact of lockdown on the local air pollution with our instrumental variable. What we identified with this instrumental variable is the effect of a prefecture's lockdown measures on air pollution if the lockdown measures were caused by the risk. Our estimates show that a prefecture's lockdown approach improves its air condition significantly. From the estimate of diff-in-diff with 2 stage-least-square (2SLS), a prefecture under lockdown reduces its air quality index by around 35%, and the estimate of diff-in-diff with OLS is only around 11%. We also find that a prefecture under lockdown reduces its PM_{10} and $PM_{2.5}$ by around 25% and 35% respectively, and the results of diff-in-diff with OLS are only around 11% and 12%. The sharp difference between diff-in-diff with 2SLS and with OLS seems to suggest that there exists substantial heterogeneity in the stringency of lockdown implementation. This further suggests that the prefectures with a high risk of COVID-19 as predicted by our instrument did not undertake stringent lockdown measures, and prefectures with a low risk of COVID-19 did undertake stringent lockdown measures. This could also be confirmed by the fact that the accumulative confirmed cases of every prefecture located in Inner Mongolia and Liaoning province totaled less than 10 until the end of March. Both Inner Mongolia and Liaoning province declared a lockdown in every prefecture in their provinces on February 10.

Given that a prefecture's lockdown significantly reduces the density of air pollutants, we still need to carefully explain the mechanism behind. A prefecture's lockdown measures limit both the mobility of a prefecture's population and the operation of its factories. Only a handful of companies in industries such as retail selling of medical supplies, medical services, and utilities were allowed to operate during the lockdown. We explore two major sources of a prefecture's air pollution: traffic and manufacturing production. To assess the effects of a traffic reduction on air pollution due to lockdown, we construct a prefecture's road intensity to capture its potential traffic volume in 2017. To capture the effects of production on pollution, we construct a prefecture's aggregate manufacturing firms' coal consumption intensity. A prefecture's aggregate manufacturing coal consumption intensity represents the dirtiness of this prefecture's production technology. If manufacturing production of a prefecture is at full capacity, more polluted technology implies worse air conditions. In other words, a prefecture is expected to experience a stronger improvement in air quality during its lockdown if it uses dirtier technology. Our estimates suggest that such prefectures experienced a stronger improvement in air conditions under lockdown, and that road intensity did not contribute significantly to the effects of lockdown on air quality.

We also investigated the heterogeneity in the effects of the various lockdown measures. By collecting the official documents about lockdown measures, we obtained the rich information of the severity of lockdown in different prefectures. For example, some low risk regions such as Yinchuan and Wuzhong tended to adopt weaker regulations like setting up checkpoints, cleaning and disinfecting the community, canceling mass gatherings and so on. Therefore, we can conduct a series of regressions to check the heterogeneous effects of various lockdown measures. we find that there are significant differences among the effects of various lockdown measures on AQI.

We provide a brief discussion herein on how our study is linked with the literature. Our paper employs daily population migration to predict a prefecture's lockdown decision, and is in close relation to the public events and migration Fang et al. (2020); Qiu, Chen, and Shi (2020); Chinazzi et al. (2020); Gray and Mueller (2012); Lu, Bengtsson, and Holme (2012).[4] Our study also relates to the literature about public environmental policy and its implications for the environment (Chen, Ebenstein, Greenstone, & Li, 2013; Davis, 2008; Viard & Fu, 2015). In addition, some recent researches studied the impacts of COVID-19 on air pollution (Dai, Hou, Liu, Zhang, & Feng, 2021; Dang & Trinh, 2021; He, Pan, & Tanaka, 2020), which are close to our research topic. We will discuss our differences and

[1] Coronavirus: Beijing purges Communist Party heads in Hubei over "botched" outbreak response in provincial capital of Wuhan https://www.scmp.com/news/china/politics/article/3050372/coronavirus-beijings-purge-over-virus-takes-down-top-communist.

[2] The inflow of population from epidemic areas has a significant impact on the outbreak of COVID-19 in a prefecture outside Hubei. In general, the first infected case in a prefecture outside Hubei had a traveling history to Wuhan before he/she was confirmed.

[3] The population flow from prefecture p' to p between January 1st and January 9th captures the relative importance of the population flow of prefecture p' to p during the pandemic.

[4] The public events in the literature referred to the epidemic, flooding, earthquake, etc.

contributions in detail in the literature review.

The remainder of the paper is organized as follows. Section 2 introduces the background of COVID- 19. Section 3 reviews the related literature. Section 4 and Section 5 describe our empirical strategy and the data sources, respectively. Section 6 presents the estimation results. Section 7 offers concluding remarks.

2. Background

2.1. The outbreak of COVID-19

The World Health Organization (WHO) has declared a global pandemic over a new coronavirus which causes an illness officially known as COVID-19. This disease has quickly spread around the world in the past months. Coronaviruses (CoV) are a large family of viruses that cause illness ranging from the common cold to more severe diseases such as Middle East Respiratory Syndrome (MERS-CoV) and Severe Acute Respiratory Syndrome (SARS-CoV). A novel coronavirus (COVID-19) is a new strain that was discovered in 2019 and has not been previously identified in humans. Therefore, human body did not have immunity against this disease and vaccine had not been developed yet. Based on the studies of 41 Chinese patients Liu, Gayle, Wilder-Smith, and Rocklov (2020) suggest that the basic reproduction number (R0) for COVID-19 in 12 studies has a mean of 3.28 and a median of 2.79. This means that the COVID- 19 is highly infectious, and one infected individual may lead three additional people to be infected on average. The findings in Huang et al. (2020) suggest that 41 patients hospitalized show high rates of respiratory distress, intensive care admission, and abnormal findings on chest computer tomography (CT) from December 2, 2019 to January 2, 2020 in Wuhan, and the death rate is 15%. Therefore, it is necessary for the government to undertake progressive measures to reduce the contact between people during the outbreak of the disease.

The epicenter in China, Wuhan, was the first prefecture to undertake a lockdown measure on January 23, 2020. The first infected case of COVID-19 was discovered in Wuhan, an inland port city with more than 11 million populations. Due to the highly infectious nature, the total number of infected cases increased tremendously. On January 23 of 2020, the central government announced to lock down the whole Wuhan city, when the documented accumulative confirmed cases in Wuhan was close to 500. This action included shutting down the cross-prefecture highway networks, ferries, high-speed railways and bus-line from and to Wuhan. Within Wuhan, restaurants, hotels, and the entertaining facilities were closed down. In the residence community in Wuhan, visitors were not allowed to go in. The residents living inside the community were only allowed to go outside three times a week for purchasing necessary groceries. These actions are believed to reduce people's contact, hence the contagion of the COVID-19. After Wuhan announced lockdown on January 23, other large prefectures outside Hubei province such as Wenzhou, Ningbo, Zhumadian, Hangzhou, Zhengzhou, Haerbin, and Fuzhou undertook similar measures, as they saw a rapidly rising number of infected cases.[5] We also observe prefectures undertaking lockdown with no more than five accumulative COVID-19 confirmed cases after the COVID-19 period. These prefectures include Yingkou, Benxi, Liaoyang, and Wuhai.

The COVID-19 has caused substantially detrimental impact on both the health of the Chinese people and local economy. Up to October 1st, 2020, the total deaths of COVID-19 in China exceed 4000 and the total number of infected cases exceed 90,000.[6] In response to the outbreak of this disease, 129 prefectures including which of Hubei (the total number of prefectures in China is 326) received a lockdown measure. Fig. A1 shows us the spatial distribution of lockdowns across different prefectures. The epicenter Wuhan located inside Hubei province, and a large number of prefectures with lockdowns located geographically close to the Hubei province. Other prefectures with lockdowns lie along the Northeastern part of China, such as prefectures from Inner Mongolia and Liaoning. The lockdown measures undertaken by the prefectures outside Hubei were not happened on the same day. Fig. A2 shows us the timing of the lockdowns by the prefectures. The prefectures undertook lockdowns gradually between January 23 and February 12. Before the Chinese New Year, January 25, only the prefectures from Hubei province undertook lockdown measures. Most of the prefectures undertook lockdown measures around February 1. Around February 5, 82 prefectures announced to undertake lockdown measures. Due to the lockdown measures around 300 million people had been affected, which consist of one fifth of the total population in China. In the meantime, around 210 prefectures announced to shut down the cross-prefectures' bus-line, ferries, and its own public transport services within the prefecture.

2.2. Dynamics of population flow and confirmed cases

2.2.1. Lockdown and population flow

What determines the lockdown policy? In our opinion, whether to take lockdown measure mainly depends on the potential threat of COVID-19. Unlike the previous epidemic, the COVID-19 spread around the world quickly in a few days and has a high mortality. In addition, the COVID-19 broke out in the lunar new year holiday, which is the most active period of migrant population in China. After China's authorities confirmed that the virus can pass from person to person on January 20, the serious threat of epidemic increased the motivation of officers to lockdown the prefecture to contain the virus's spread. Although the prefecture's lockdown timing was affected by a lot of other factors including the development of local economy, the proportion of travelers choosing public transportation, its

[5] Wenzhou was locked down on February 2, 2020; Ningbo, Zhumadian, Hangzhou, Zhengzhou, Haerbin, and Fuzhou were locked down on February 4, 2020.

[6] http://www.nhc.gov.cn/cms-search/xxgk/getManuscriptXxgk.htm?id=08c7b372eece40b3acaa46f03c738f69.

real-time resources and the local official's taste and ability to deal with the public health event. From the timing of lockdown and the characteristics of the prefectures with lockdown, we can conclude that the prefecture's exposure to the COVID-19 risk is the major factor to promote the lockdown decisions. In addition, under the conditions of the limited data, this factor is the most appropriate for constructing an exogenous instrumental variable.

The lockdown measure substantially limited the mobility of the people within a prefecture. According to the Baidu migration data, a prefecture's mobility intensity which captures the flow of population within the prefecture experienced a stronger reduction for the prefectures undertaking lockdown measures during the Spring Festival which lasted from January 23 to February 9 in China. Fig. A3 shows us the dynamics of mobility intensity in prefecture groups with and without lockdown measures. We split the prefectures into two groups depending on their choice of undertaking lockdown measures before February 29. We also define a group of prefectures with lockdown measures as treatment group and all the other prefectures as control group. From our definition, the prefectures inside the treatment or control group does not vary over time. From this figure, the treatment group, which is in solid line, had a relatively high mobility intensity before January 23. After January 23, the mobility intensity dropped for prefectures in both the treatment and control groups, and the prefectures in the treatment group experienced a much stronger reduction, which means that the mobility of population inside the prefecture was more restrictive for the treatment than the control group.

The lockdown measures also limit flow of population across prefectures. According to the daily immigration and outmigration scale of prefectures from the Baidu data, the migration scale reduced substantially during the outbreak of the COVID-19 in China. Fig. A4 presents the dynamics of the population flow across different prefectures for 2019 and 2020. The two upper panels in this figure report the average outflow (left) and inflow (right) in 2020. The two upper panels show that both the daily outflow and inflow of population experienced a reduction in our study period. The reduction of both outflow and inflow of population is much sharper for the prefectures with lockdown measures than the ones without these measures. As a comparison, we show the inflow and outflow of population in 2019 for the two prefecture groups in the lower panels of Fig. A4. From these lower panels, the dynamics of population flow for both prefecture groups are similar.

2.2.2. Dynamics of the confirmed case

To estimate the effects of a lockdown on the COVID-19 related health outcomes, we employ our framework which is discussed fully in the previous section. The data of COVID-19 outcomes comes from the National Health Commission of China, which reports the accumulative confirmed cases, deaths and recovery. We are interested in the number of daily new cases, and hence we calculate a prefecture's daily new COVID-19 related outcomes by taking the difference of the accumulative outcomes between two days. Fig. A5 shows us the dynamics of the daily new confirmed cases across different prefectures in China outside Hubei province. This figure shows that the average daily new case peaks at the beginning of February, before the massive lockdown measures took place.

3. Related literature

This paper exploits the population migration between the epicenter and a prefecture to predict the optimal lockdown action of this prefecture. Our paper is in close relation to the public events and migration. Fang et al. (2020) and Qiu, Chen, & Shi (2020) use the outmigration from the epicenter in China, Wuhan, to a prefecture, to predict this prefecture's infected cases. Chinazzi et al. (2020) propose to use a Global Epidemic and Mobility model to study the impact of travel limitation on the national and international spread of the COVID-19. Gray and Mueller (2012) investigate the consequences of climate-related natural disasters for long-term population mobility in rural Bangladesh, and find that flooding had modest effects on mobility that are most visible at moderate intensities and for women and the poor. Lu et al. (2012) analyze the movements of 1.9 million mobile phone users during the period from 42 days before, to 341 days after the devastating Haiti earthquake of January 12, 2010. Their findings suggest that population movements during disasters may be significantly more predictable than previously thought. Our study is different from the literature in the sense that we use the population migration from the epicenter to predict the optimal lockdown action outside the epicenter.

Our study is also related to the literature about public policy and its implication for the environment. Viard and Fu (2015) evaluate the pollution and labor supply reductions from Beijing's driving restrictions. Beijing's driving restrictions reduced air pollution but at the cost of less work time by those with discretionary labor supply. Chen, Ebenstein, et al. (2013) show that an arbitrary Chinese policy that greatly increases total suspended particulates (TSPs) air pollution caused the 500 million residents of Northern China to lose more than 2.5 billion life years of life expectancy. Chen, Jin, et al. (2013) show that the actions from the Chinese government to reduce traffic flow and production during and a little after the Beijing Olympic Games significantly improved the air quality. Almond, Chen, Greenstone, and Li (2009) find that the heating policy led to dramatically higher pollution levels in the North China. Davis (2008) shows that the travel restrictions in Mexico have no effect on improving air quality. Our identification is different from the literature in the sense that we address the potential endogenous problem of a lockdown by the local government using the daily bilateral migration information in China. Our identification strategy substantially alleviates the potential political concern to the decision of a lockdown.

The most relevant works to our paper are the researches of He et al. (2020), Dang and Trinh (2021) and Dai et al. (2021). He et al. (2020) used the DID approach to examine the short-term impacts of COVID-19 on air pollution in China. Dang and Trinh (2021) offer an early assessment with cross-national evidence on the causal impacts of COVID-19 on air pollution by using a regression discontinuity design approach. And Dai et al. (2021) applied machine learning to quantify the impacts of the COVID-19 lockdown as well as the Chinese Spring Festival (CSF) holidays on the air quality changes in 31 major Chinese cities. Our paper joints the discussion of the environmental impact of COVID-19 by contributing in the followings: (1) Introducing a new instrumental variable to address the potential endogenous concerns. In order to address the endogenous concerns, we exploit the population flow from the epidemic area to construct an instrument variable, which could also capture the unobservable COVID-19 risk from the perspective of the local governments. Our results suggest massive difference in estimates with and without our IV, which seems to confirm our guess. (2) We also examine the longer-term effects of COVID-19 lockdown, which is not shown in the previous paper.

4. Empirical strategy

In this section, we propose to use a diff-in-diff identification strategy to identify the impacts of a prefecture's lockdown. The challenge of identification is that a prefecture's lockdown decision may not be random, because local politicians are concerned with their promotion opportunities, which are closely linked with local economic performance (Li & Zhou, 2005). If a politician undertakes radical isolation measures, he or she is aware that such measures may substantially slow the growth of the economy. Therefore, local politicians may have no incentive to impose lockdown measures. Additionally, we find that prefectures under lockdown were not the ones with the highest number of cases. For example, each prefecture in Liaoning province, with no more than 10 confirmed cases, undertook lockdown measures. Yet the average confirmed cases across different prefectures outside Hubei was around 40 as of the end of March, far higher than 10. Therefore, we expect to observe substantial heterogeneity with respect to the stringency of lockdown measures across prefectures.

To address this issue, we predict a prefecture's lockdown decision outside Hubei according to inflow of population from prefectures with an epidemic. Fang et al. (2020) suggests that a prefecture's inflow of population from Wuhan contributes significantly to its accumulative number of confirmed COVID-19 cases. We extended this measure by first identifying a prefecture p' to be an epidemic area at time t if its accumulative number of confirmed cases is higher than a certain threshold $\overline{C}$. A prefecture is subject to high risk of COVID-19 outbreak and should undertake lockdown measures if it receives a substantial inflow of population from epidemic areas. To capture the bilateral population flow from one prefecture p' to another one p and avoid the potential endogenous problem, we use their population flow two weeks before Wuhan's lockdown which marked the outbreak of COVID-19 in China (January 23rd). This bilateral population flow is meant to capture the daily commuting flow across different prefectures. We do not use a place's real-time population inflow from an epidemic area because the real-time population flow is likely to be affected by other COVID-19 related measures such as highway closures or the shutting down of cross-prefecture bus lines. Therefore, our instrumental variable (IV) is as follows:

$$\widehat{M}_{pt} = \sum_{t' < t} \sum_{p'} I\left(Case_{p' t'} \geq \overline{C}\right) M_{p' p, t_0}$$

where $I\left(Case_{p' t'} \geq \overline{C}\right)$ is a dummy variable equal to 1 if the number of confirmed cases of prefecture p' at time t is larger than $\overline{C}$, $M_{p'p,\ t0}$ captures the average bilateral flow of population from prefecture p' to prefecture p between January 1 and January 9, 2020, and $\widehat{M}_{pt}$ captures the potential threat of COVID-19 via population inflow. Another problem here is that $\widehat{M}_{pt}$ becomes larger as date index t increases. So we think of using the daily average $\frac{\widehat{M}_{pt}}{t}$ as the final instrument.

The potential COVID-19 threat to prefecture p depends on the past inflow of population from prefecture p' and its confirmed cases. $M_{p'p,\ t0}$ captures the relative importance for p of population flow from p'. If there was a large population flow from p' to p before the outbreak of COVID-19, prefecture p' is expected to have a non-negligible population flow to p after the outbreak of COVID-19. Here, we assume that a prefecture's lockdown decision does not affect its past population inflow, which is captured by $M_{p'p,\ t0}$. Before January 9, a prefecture outside Hubei was less incentivized to manipulate population inflow. This is because January 9th is one day before the beginning of "Chunyun," the Spring Festival travel season, when there is a large population flow from one prefecture to another for the celebration and reunion.

Politicians outside of Hubei may have been less aware of the detrimental effects of COVID-19 on people's health and the economy before the Spring Festival. Also, prefecture p's lockdown decision might not have affected the accumulative number of confirmed cases in another prefecture p'. Our instrumental variable might also capture the relative stringency of lockdown measures, if more stringent measures were implemented in prefectures with higher risk of a COVID-19 outbreak.

Using a prefecture's risk of a COVID-19 outbreak, we estimated the following equation to generate a prediction for a prefecture's lockdown decision, which is also the first stage of our 2SLS estimation:

$$I\left(event_{pt} = 1\right) = \beta_0 + \frac{\beta_1 \widehat{M}_{pt}}{t} + \alpha_t + \alpha_p + \epsilon_{pt} \tag{1}$$

where $I(event_{pt} = 1)$ is a dummy variable that takes a value of 1 if prefecture p undertook lockdown measures at date t. With this approach, we could predict the probability that prefecture p underwent a lockdown depending on the potential threat of COVID-19 via population inflow.

Our instrumental variable allowed us to capture both the location and timing of a lockdown measure, depending on population inflow. If there was a past non-negligible flow of population from the potential epidemic area to prefecture p, prefecture p is expected to undertake lockdown measures. If the number of confirmed cases increases rapidly in the potential epidemic area, such that it quickly exceeds the threshold number C, this prefecture p is expected to implement earlier lockdown measures. We use the Baidu Migration Index to measure the population flow from one prefecture to another. The Baidu Migration Index provides daily information on the bilateral traveling population across different prefectures in China.

With the predicted probability of a lockdown, we adopted a diff-in-diff approach to evaluate the impact of lockdown measures on the environment. We used a dummy variable to measure whether a prefecture announced lockdown measures at time t. If prefecture p

undertook lockdown measures on date t, then it kept these measures till the end, implying March 31 of 2020 in our study.

$$ln(y_{pt}) = \alpha_p + \alpha_t + \gamma_0 \widehat{I}(event_{pt} = 1) + \epsilon_{pt} \tag{2}$$

where y_{pt} represents the outcome of interest for prefecture p at date t, α_p represents the prefecture fixed effects, and α_t represents the time fixed effects.

According to Imbens (2014), a valid instrumental variable has to satisfy two criteria: (1) The instrument is correlated with the endogenous variable, and (2) the instrument affects the dependent variable only indirectly, also known as the exclusion restriction. The correlation between the endogenous variable and the instrumental variable has been discussed in our construction process and will be tested statistically by conducting a first-stage F-test, which will been shown in Section 6. As for the exclusion restriction, it is hard to test whether or not the instrument is uncorrelated with the error term. We argue that potential threat of COVID-19 via population inflow between January 1 and January 9, 2020 is not directly related to the air quality of prefectures, but has the indirect effect by influencing the prefecture's lockdown decision. Given that the confirmed cases outside a prefecture can hardly be correlated with the air of this prefecture, the main concern for our exclusion restriction is that the transportation supplied for the population flow will affect a prefecture's environment. To deal with the problem, we adopted the past average inflow of population between January 1 and January 9, 2020 to capture the potential threat of COVID-19, which would not affect the transport activities later. Another evidence to support the exclusion restriction is that we find that the within-prefecture migration in prefectures with lockdown and which without lockdown had no significant difference. So our instrument do not affect our outcomes through channels other than the lockdown. Nevertheless, there are still some limitations in our construction. First, the accumulated flows between other prefecture with COVID-19 cases are not equivalent to COVID-19 risk. Second, we cannot control other factors which could affect the lockdown decision. Indeed, our instrument is not fully equal to the COVID-19 risk, and it is hard to measure other determinants due to the lack of daily data, but all we need for identification is a reliable exogenous variation. And our instrument could serve as a valid instrument to capture the potential risk of COVID-19, although it is not perfect.

5. Data

5.1. Documents from local offices

The first dataset we use comes from the official documents that report measures of the local government in response to the outbreak of the COVID-19. We manually collect all the related documents from the local offices. These documents report the date when they announce to undertake the lockdown measures. In addition, these documents also report specific measures, such as shutting down the public transport services and curfews. We have collected documents for around 130 different prefectures, which officially announced lockdown measures. The list of Locked-down prefectures is reported in Table A1. Table A1 also describes the stringency of lockdown measures undertaken by prefectures, which can help to discuss the heterogeneity in the effect of lockdown measures on air pollution.

5.2. Annual environmental survey of polluting firms (AESPF)

The data on firms' pollution emissions comes from the Annual Environmental Survey of Polluting Firms (AESPF) of China. It includes rich information on firms' environmental performance such as main pollutants emissions (waste water, industry exhaust, COD, SO_2, soot and dust, etc.), pollution abatement (sulfur dioxide removal, soot removal, desulfurization device, etc.), and energy consumption (fuel coal, fuel oil, raw coal and industrial fresh water, etc.), among others. Since the "Tenth Five- Year Plan" in 2001, the scope, frequency, main indicators and reporting methods of the environmental survey have basically become stabilized. As long as a firm's discharged pollutants are in the top 85% of the total pollutant discharge at the county level, this firm is included in the key-point environmental survey list, and it must send a unified environmental report to the environmental authorities every year. After review and verification by relevant administrative departments, these data are entered into the database. This article uses the main fuel indicators in the database.

5.3. Population migration data

We obtain daily bilateral prefecture population flows from Baidu Migration, a electronic navigating map run by the largest Chinese search engine, Baidu. Baidu can map the migration trajectory of mobile phone users by analyzing the location information of mobile phone users through the Location Based Service (LBS) open platform. There are currently more than 500 million mobile Internet users in China, and Baidu's LBS open platform's location services cover hundreds of thousands of apps, and the number of location requests per day exceeds billions. So the location information data provided by Baidu Migration is undoubtedly the most convincing in China. The Baidu Migration data set covers 120,142 pairs of prefectures per day for 364 Chinese prefectures between January 12 and March 31 in 2019, and between January 1 and March 31 in 2020. Note that, by the lunar calendar, the data covers the same period of 24 days before and 54 days after the Chinese New Year, respectively for year 2019 and year 2020. In addition, Baidu offers information on the daily population mobility intensity within the prefecture, and this is a panel sample with more than 20 thousand observations each year.

Table 1
Summary statistics of data.

	All prefectures	2020 (01. January - 31. March)			2019 (12. January - 13. April)	
		Treatment group		Control group	Treatment group	After Treatment
		Before Treatment	After Treatment			
Panel A: Environment data						
AQI	73.04	89.34	61.07	73.36	81.10	82.11
	(48.46)	(55.96)	(25.49)	(51.44)	(45.74)	(56.12)
$PM_{2.5}$	45.98	64.05	35.52	45.33	54.50	52.26
	(40.47)	(47.94)	(21.54)	(42.15)	(39.58)	(48.22)
PM_{10}	70.12	81.66	59.15	71.23	84.39	90.06
	(72.71)	(56.49)	(35.29)	(84.52)	(51.01)	(103.02)
Panel B: Health data						
Confirmed cases	27.75	9.23	74.28	15.75	–	–
	(77.29)	(40.48)	(142.06)	(31.67)	–	–
New confirmed cases	0.49	1.33	0.54	0.26	–	–
	(2.98)	(5.75)	(2.56)	(1.91)	–	–
Cured cases	18.73	0.24	53.51	10.89	–	–
	(59.21)	(1.98)	(110.79)	(26.04)	–	–
New cured cases	0.48	0.06	1.34	0.27	–	–
	(2.29)	(0.48)	(4.15)	(1.36)	–	–
Panel C: Migration data						
Within-prefecture migration	3.92	4.47	3.81	3.83	4.71	4.43
	(1.34)	(1.55)	(1.22)	(1.29)	(0.76)	(0.78)
Outflow	0.75	1.64	0.71	0.55	1.80	0.89
	(1.32)	(2.83)	(0.78)	(0.64)	(2.33)	(0.88)
Inflow	0.75	1.45	0.80	0.56	1.83	0.87
	(1.02)	(1.63)	(1.09)	(0.66)	(2.39)	(0.88)
Prefectures	314.00	117.00	117.00	197.00	117.00	197.00

Notes: This table mainly reports the mean values and standard deviations of different variables at the daily level.

5.4. Pollution and weather data

Daily air quality data were collected from the records of 1650 local monitoring stations and each monitor reports the air quality index and intensity of pollutants in the air. This dataset reports the concentration of coarse particulate matter (PM_{10}), fine particulate matter ($PM_{2.5}$), carbon monoxide (CO), sulfur dioxide (SO_2) and nitrogen oxides (NO_X). A general concern is that the local government in China has incentives to manipulate the local air quality data because the performance of the local air quality affects substantially his or her promotion possibility (Ghanem & Zhang, 2014). However, this concern has been significantly alleviated as the China upgraded its air quality monitoring system to measure pollutants more precisely. This newly adopted monitoring system gathers pollutant sample automatically and at the same time reports the results. So the newly adopted system significantly improved the air quality as shown by Greenstone et al. (2020), because this monitoring system makes it very difficult for the local government to manipulate the air pollution data. Our air quality data covers all the monitoring stations in China. if a prefecture has multiple monitoring stations, we will take the arithmetical mean of them as the prefecture's outcome.

Table 1 reports the summary statistics for the air pollution, cases and migration data. As seen from the Panel A, the lockdown prefectures were, on average, more polluted than the control prefectures before the lockdowns. And we can see a sharp decline in all air pollutants concentrations due to the lockdown. From the Panel B, we found that the new confirmed cases experienced a decline and the new cured cases gone up, on average, after the lockdown. Panel C shows that the lockdown prefectures experienced a strong reduction in both the within-prefecture migration and cross-prefecture migration.

6. Empirical results

6.1. Estimation results for the environment

6.1.1. Estimates with diff-in-diff

The threat of COVID-19 on a prefecture depends on how we define an epidemic area, which links with the value of $\overline{C}$. The value of $\overline{C}$ determines prefecture p's risk of COVID-19 exposure. If we choose a relatively lower value for $\overline{C}$, a larger number of prefectures would be considered epidemic areas. This implies that a prefecture with population inflow from many different prefectures has a high risk of exposure to COVID-19. On the other hand, if we choose a relatively higher value for $\overline{C}$, a smaller number of prefectures will be considered epidemic areas. This implies that a prefecture with population inflow from many different prefectures could balance out the risk of COVID-19. As shown in the appendix, our estimates are robust to a reasonable variation of $\overline{C}$.

We find that the average local accumulative number of confirmed cases on the day when the lockdown started is around 48. Therefore, we tried several values, namely 5, 10, 30, 50, 80, and 100, for $\overline{C}$ to run the first stage. We show our results for the second

Table 2
The impact of a prefecture's lockdown on the environment.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Results in the first stage						
Dependent variable: $I(event_{pt} = 1)$						
$\widehat{M}_{pt,5}$	0.00193***					
	(0.00)					
$\widehat{M}_{pt,10}$		0.00202***				
		(0.00)				
$\widehat{M}_{pt,30}$			0.00230***			
			(0.00)			
$\widehat{M}_{pt,50}$				0.00276***		
				(0.00)		
$\widehat{M}_{pt,80}$					0.00341***	
					(0.00)	
$\widehat{M}_{pt,100}$						0.00408***
						(0.00)
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Date-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.687	0.685	0.681	0.680	0.678	0.677
F-value	51.48	52.21	42.46	35.50	29.76	20.52
Observations	28,574	28,574	28,574	28,574	28,574	28,574
Panel B: Results for *AQI*, *PM₁₀* and *PM₂.₅* in the second stage						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables:	ln(*AQI*)	ln(*AQI*)	$\ln(PM_{10})$	$\ln(PM_{10})$	$\ln(PM_{2.5})$	$\ln(PM_{2.5})$
$I(event_{pt} = 1)$	−0.109***	−0.348**	−0.109***	−0.245*	−0.116***	−0.345**
	(0.00)	(0.16)	(0.00)	(0.13)	(0.00)	(0.18)
ESt.	OLS	2SLS	OLS	2SLS	OLS	2SLS
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Date-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,574	28,574	28,574	28,574	28,574	28,574

Notes: Standard errors are in parentheses and clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Weather controls include daily temperature, its square, humidity, and precipitation. $I(event_{pt} = 1) = 1$ if a prefecture p undertook a lockdown at day t. Otherwise, $I(event_{pt} = 1) = 0$. $\widehat{M}_{pt,\overline{C}}$ refers to the threat of COVID-19 of prefecture p at day t with $\overline{C} \in \{5, 10, 30, 50, 80, 100\}$. We choose 30 for the value of $\overline{C}$ in the second stage. *ln* (*AQI*) represents the log value of a prefecture's air quality index, $\ln(PM_{10})$ represents the log value of a prefecture's coarse particulate matters (μg/m^3), $\ln(PM_{2.5})$ represents the log value of a prefecture's fine particulate matters (μg/m^3).

stage estimation with $\overline{C}$, and the results are robust if we choose $\overline{C}$ from 5 to 100. Panel A of Table 2 reports the results for all the threshold values of $\overline{C}$, and they are all significant and positive. Column (1) of this table shows that a one-unit increase in prefecture p's threat of COVID-19 is associated with a 0.2% increase in this prefecture's probability of announcing a lockdown. As we increase the threshold value for $\overline{C}$, the significance does not change, and the correlation between a prefecture's threat and its lockdown behavior increases. Column (6) shows that a one-unit increase in a prefecture's threat of COVID-19 is 0.4% associated with a prefecture's lockdown decision, when we choose 100 for the value of $\overline{C}$.

Table 2 reports the estimates of the first stage in panel A and the estimates of the second stage for PM_{10}, $PM_{2.5}$, and *AQI* in panel B. Here, we choose 30 for the value of $\overline{C}$, which is close to the average accumulative confirmed cases as of the end of March. Column (2) shows that a prefecture's lockdown measures reduced its *AQI* by around 35% with diff-in-diff IV, and column (1) shows that a prefecture's lockdown measures reduced its *AQI* by around 11% with diff-in-diff with OLS. Column (4) suggests that a prefecture's lockdown reduced its density of PM_{10} by around 25%. A prefecture's Lockdown reduced its density of $PM_{2.5}$ by around 35%. which is similar to the effects on *AQI*.

So, what can we learn from this exercise? The estimates of diff-in-diff with OLS treat every prefecture as the same as long as this prefecture announced a lockdown with an official document. In the OLS regression, what we estimated is the simple correlation between a prefecture's lockdown and air condition, with which we could not interpret as causal. But in the 2SLS regression, we adopted an instrument to capture the relative stringency of lockdown among the prefectures according to the COVID-19 risk, which can reflect the intensity of policy implementation. When a prefecture faced with higher risk, the local government had a stronger incentive to strengthen the enforcement of lockdown. Our results have confirmed this argument. The estimates of 2SLS were much larger than the estimates of OLS, suggesting that a prefecture with a higher risk of COVID-19 is associated with a more substantial reduction in air pollution after lockdown. In *Section 6.3.2*, we provide estimates with the same framework but taking into account the log value of real-time population inflow. The estimates are robust.

Table 3
The potential channels that contribute to the effects of a lockdown on the environment.

	(1)	(2)	(3)	(4)
Dependent variables:	ln(*AQI*)	ln(*AQI*)	ln(*AQI*)	ln(*AQI*)
$I(event_{pt}=1)$	−0.348**	−0.887*	0.458*	0.159
	(0.16)	(0.51)	(0.24)	(0.46)
$I(event_{pt}=1) \times Road_{pt_0'}{}^{den}$		0.36		0.16
		(0.23)		(0.20)
$I(event_{pt}=1) \times Coal_{pt_0'}{}^{den}$			−2.21***	−2.45***
			(0.49)	(0.36)
$I(event_{pt}=1) \times Population_{pt_0'}$		0.00	−0.00	−0.00
		(0.00)	(0.00)	(0.00)
Est.	IV	IV	IV	IV
Weather controls	Yes	Yes	Yes	Yes
Prefecture-fixed effects	Yes	Yes	Yes	Yes
Date-fixed effects	Yes	Yes	Yes	Yes
Observations	28,574	28,574	28,574	28,574

Notes: Standard errors are in parentheses and clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Weather controls include daily temperature, its square, humidity, and precipitation. $I(event_{pt}=1)=1$ if a prefecture *p* undertook a lockdown at day *t*. Otherwise, $I(event_{pt}=1)=0$. $Road_{pt0'}{}^{den}$ refers to the initial road intensity of prefecture *p*, $Coal_{pt0'}{}^{den}$ refers to the average initial manufacture firms' coal consumption intensity of prefecture *p*, and $Population_{pt0'}$ refers to the initial population of prefecture *p*.

6.1.2. Potential mechanism

Given that a prefecture's lockdown substantially reduces its air pollution, we examine the possible role of manufacturing production and traffic. Chen, Ebenstein, et al. (2013) show that limiting the flow of daily traffic and the shut-down of manufacturing plants contributed substantially to Beijing's air quality during the 2008 Olympic Games. Following this idea, we use a prefecture's average coal consumption intensity, i.e., the ratio between coal consumption and sales, in 2010 from AESPF to measure the dirtiness of production at the prefecture level.[7] If a prefecture has a relatively higher coal consumption intensity, this means that the production of this prefecture relies heavily on coal as fuel in production. To capture the effect of reduced traffic due to lockdown measures, we use a prefecture's road intensity in 2017, i.e., the ratio between a prefecture's total road length and its population. To implement this idea, we estimate the following equation:

$$ln(y_{pt}) = \alpha_p + \alpha_t + \xi_0 \widehat{I}(event_{pt}=1) + \xi_1 \widehat{I}(event_{pt}=1) \times Road^{den}_{pt_0'} + \xi_2 \widehat{I}(event_{pt}=1) \times Coal^{den}_{pt_0'} + \epsilon_{pt} \tag{3}$$

where $Road_{pt_0'}{}^{den}$ captures the road density of prefecture *p* at the initial period t_0' and $Coal_{pt_0'}{}^{den}$ captures the coal intensity of the manufacturing firms of prefecture *p* at time t_0'. We expect both the estimates for ξ_1 and ξ_2 to be negative and significant. A prefecture with dirtier production technology or a high volume of traffic is expected to experience a greater reduction in pollution once under lockdown.

Table 3 reports the results of the estimates, controlling for the size of a prefecture in terms of its population. These estimates help us understand the extent to which traffic and manufacturing production contribute to the effects of a lockdown on the environment. Column (2) shows that a prefecture with a high initial level of road intensity does not have a stronger reduction in pollution. Column (3) shows that manufacturing firms' coal consumption intensity within a prefecture absorbs nearly all the effects of that prefecture's lockdown on the environment, indicating that the effects of a prefecture's lockdown are due to a reduction in manufacturing production. This argument can be confirmed if we put all the interaction terms into one regression as shown in column (4). In column (4), only the interaction term between coal consumption intensity and the lockdown dummy is significantly negative.

6.2. The heterogeneity in the lockdown measure

It's important to note that the stringency of lockdown was totally different from the heterogeneity in the lockdown measure. The former could not be observed directly but could be taken into account in our 2SLS regressions. The latter could be found in the official documents about lockdown. We demonstrated the specific lockdown measures in different prefectures in Table A1. Beyond those common measures, including setting up checkpoints, cleaning and disinfecting the community, canceling mass gatherings, the 117 prefectures adopted different actions to prevent the virus from further spreading. Because these measures are not comparable and heterogenous, we cannot treat them as the variable treatment intensities. Thus the identification strategy with variable treatment intensity (Angrist & Imbens, 1995) is not suitable for our question.

Even so, the rich information of official documents can help us investigate the heterogeneity of different measure's effect on air pollution. Hence we conducted a set of regressions by changing the dependent variable in first stage for checking the heterogeneous effects of various lockdown measures. The results are represented in Table 4, where $I(measure_{ipt}=1)$ is a dummy variable that takes a value of 1 if prefecture *p* undertook the lockdown $measure_i$ at date *t*. We found that there are significant differences among the effects of

[7] We assume that the relative dirtiness of technology in 2010 could reflect the relative dirtiness of technology today.

Table 4
The heterogeneous effects of different lockdown measures.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variables:	ln(*AQI*)	ln(*AQI*)	ln(*AQI*)	ln(*AQI*)	ln(*AQI*)	ln(*AQI*)	ln(*AQI*)	ln(*AQI*)	ln(*AQI*)	ln(*AQI*)	ln(*AQI*)	ln(*AQI*)
$I(measure_{ipt} = 1)$	−0.366***	−0.522***	−0.498***	−0.505***	−1.074**	−0.354***	−0.531***	−0.572***	−0.374***	−0.746***	−1.602	−1.118**
	(0.108)	(0.188)	(0.167)	(0.179)	(0.521)	(0.109)	(0.159)	(0.194)	(0.114)	(0.256)	(1.145)	(0.482)
Est.	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,574	28,574	28,574	28,574	28,574	28,574	28,574	28,574	28,574	28,574	28,574	28,574

Notes: Standard errors are in parentheses and clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. $I(measure_{ipt} = 1) = 1$ if a prefecture p undertook a $measure_i$ at day t. Otherwise $I(measure_{ipt} = 1) = 0$. The specific lockdown measures are as follows: 1) Contactless delivery; 2) Communities with confirmed cases may implement closed isolation; 3) All visitors and exotic vehicles are not allowed to enter the community; 4) Travelers from the Epidemic Area Need to be Quarantined for 14 Days upon Arrival to the Prefecture; 5) Close contacts need to be quarantined at assembly sites; 6) Public places not necessary for the lives of residents should be closed; 7) Suspension of non-essential project; 8) Communities should strengthen management of rental housing; 9) Persons Stranded in the Epidemic Area Could not Return; 10) Health QR code or pass shall be used to manage people; 11) Wedding suspended and funeral simplified; 12) Each family (exclude home quarantine families) could only assign one family member to purchase daily supplies every two/three days.

Table 5
The long-term effect of the lockdown measure.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables:	ln(*AQI*)	ln(PM_{10})	ln($PM_{2.5}$)	ln(SO_2)	ln(NO_2)	ln(*CO*)
$I(event_p = 1)$	0.0268	0.0286	0.0479	0.0791*	0.103***	0.00201
	(0.0305)	(0.0378)	(0.0376)	(0.0437)	(0.0373)	(0.0242)
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Date-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	111,360	111,360	111,360	111,360	111,360	111,360

Notes: Standard errors are in parentheses and clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Weather controls include daily temperature, its square, humidity, and precipitation.

Table 6
The impact of a lockdown on the environment (levels).

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables:	*AQI*	*AQI*	PM_{10}	PM_{10}	$PM_{2.5}$	$PM_{2.5}$
$I(event_{pt} = 1)$	−10.95***	−42.21**	−14.77***	−45.34**	−7.07**	−27.44*
	(3.60)	(18.87)	(4.53)	(20.80)	(2.77)	(14.60)
Est.	OLS	2SLS	OLS	2SLS	OLS	2SLS
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Date-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,574	28,574	28,574	28,574	28,574	28,574

Notes: Standard errors are in parentheses and clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *AQI* measures the absolute value of a prefecture's air quality index, PM_{10} measures the absolute value of a prefecture's coarse particulate matters density (μg/m^3), $PM_{2.5}$ measures the absolute value of a prefecture's fine particulate matters density (μg/m^3). Weather controls include daily temperature, its square, humidity, and precipitation.

various lockdown measures on *AQI*. Among these measures, $measure_{12}$ had the biggest positive effect on air pollution, which reduced the *AQI* by around 112%. The results were correspondent with our expectation. Because the $measure_{12}$ stipulated that each family (exclude home quarantine families) could only assign one family member to purchase daily supplies every two/three days, and other citizens were not allowed to go out except for medical treatment, epidemic prevention and control, and working with the approval of local government. This regulation severely restricted the movement of people and production, and thus could reduce air pollution more significantly compared with other measures.

6.3. The long-term effect of the lockdown measure

When the COVID-19 epidemic started to slow down in China in late February, most prefectures started to cancel the lockdown measures. Although lockdown is a short-run Decision, whether it will cause a long-lasting effect excites our interest. In order to analyze this problem, we extended our sample period to March 31, 2021. Because all the prefectures cancelled the lockdown policy after March of 2020, what we can identify is just the coefficient of a dummy, which equal to 1 if a prefecture ever took the lockdown measure. Table 5 reports the results on the long-term effect of the lockdown measure. In the long run, the effect of lockdown on air quality has faded away. This suggests that the lockdown only improve the air quality in the short-term.

6.4. More robustness checks

6.4.1. Event study

We first evaluate the impacts of a prefecture's lockdown measure using an event study framework. A government is identified to undertake a lockdown approach if it declared to adopt a lockdown measure via an official document. To assess the impact, we compare the trends of the prefectures with lockdown measures to those without lockdown measures in the following specification:

$$ln(y_{pt}) = \alpha_p + \alpha_t + \sum_{j=-30}^{30} \beta_j \widehat{I}(event_{pt} = 1) + \epsilon_{pt}$$

This specification includes prefecture (α_p) and time (α_t) fixed effects. Standard errors are clustered at the prefecture level where the shocks generally happen.

Fig. A6 displays the results of the event study about environment graphically. The first panel in Fig. A6 shows us the results of log of *AQI*. Before the event, our results suggest that the prefectures with lockdown are systematically more polluted. After a prefecture undertook a lockdown, the estimates for the effects of lockdown on *AQI* became more apparent. After the first week, the estimates are

Table 7
Robustness check by including the samples of 2019.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables:	*ln(AQI)*	*ln(AQI)*	$ln(PM_{10})$	$ln(PM_{10})$	$ln(PM_{2.5})$	$ln(PM_{2.5})$
$I(event_{pt} = 1)$	−0.348**	−0.392***	−0.245*	−0.388***	−0.345**	−0.475***
	(0.16)	(0.13)	(0.13)	(0.14)	(0.18)	(0.15)
Est.	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Date-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,574	57,148	28,574	57,148	28,574	57,148
Year Covered	2020	2019, 2020	2020	2019, 2020	2020	2019, 2020

Notes: Standard errors are in parentheses and clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Weather controls include daily temperature, its square, humidity, and precipitation. "Year Covered" refers to the sample year we use to estimate our results.

Table 8
Robustness check by including the actual inflow scale as a control variable.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables:	*ln(AQI)*	*ln(AQI)*	$ln(PM_{10})$	$ln(PM_{10})$	$ln(PM_{2.5})$	$ln(PM_{2.5})$
$I(event_{pt} = 1)$	−0.348**	−0.465***	−0.245*	−0.523***	−0.345**	−0.362**
	(0.16)	(0.14)	(0.13)	(0.16)	(0.18)	(0.15)
$ln(M_{p,\ t})$		0.099***		0.149***		0.129***
		(0.02)		(0.02)		(0.02)
Est.	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Date-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,574	28,574	28,574	28,574	28,574	28,574

Notes: Standard errors are in parentheses and clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Weather controls include daily temperature, its square, humidity, and precipitation. $ln(M_{p,\ t})$ represents the log value of total population inflow of prefecture *p* at day *t*.

significant and negative, which implies that a prefecture's lockdown improve the air condition significantly. The results of PM_{10} and $PM_{2.5}$, shown in the second and the third panel, are similar to the results of *AQI*.

6.4.2. Robustness checks

6.4.2.1. The effect of a prefecture's lockdown on the absolute value of the pollutants. Table 6 reports the estimates of a prefecture's lockdown on the absolute value of air pollution. The results show that a prefecture's lockdown reduces its *AQI*, PM_{10} and $PM_{2.5}$ by around 42 units, 45 units and 27 units using diff-in-diff with 2SLS, respectively. The results using diff-in-diff with OLS are less than one-third of which with 2SLS for all of these variables. These are consistent with what we find in the relative changes.

6.4.2.2. We also include the samples of 2019 into the regression. Given that our estimates using the time period from January 1 to March 31 of 2020, which marks the end of COVID-19 in China. We use different time periods to compare our estimate to check whether our approaches are sensitive to timing. In order to do this, we first try January 1 of 2020 to March 31 of 2020. The reason why we use this time period is that the daily new confirmed cases of prefectures outside Hubei almost fell to 0 at the end of March. In another setting, we also include the same period in 2019. In this setting, we expand our control group. Since COVID-19 did not happen in the same period of 2019, we manually set a prefecture risk of COVID-19 to be 0. Table 7 reports these estimates. The columns in odd number include only the samples from 2020, and the columns in even number include samples both from 2020 and 2019. The estimates for the three dependent variables do not vary too much between two samples, as shown in the table.

6.4.2.3. We also include the log value of actual inflow scale as a control variable. The sharp difference between the estimates using 2SLS and OLS indicates the heterogeneous effect of lockdown on the environment. Nevertheless, there is still concern that the exclusion assumption of our IV is not satisfied because that the inflow of population from epidemic areas might affect pollution other than lockdown. Since it is not possible to test this exclusion assumption directly, we control for the log value of actual inflow of population in our regression and check whether our estimate is robust. Table 8 reports these results. The columns in even number of this table report the results adding this control variable. Our estimate shows that adding this control variable does not change our diff-in-diff with 2SLS estimates too much.

6.4.2.4. We estimate the effects of a prefecture's lockdown with various $\overline{C}$. Given that we only use $\overline{C} = 30$ in our main text, it is tempting to know how our estimates would be affected if different $\overline{C}$ is chosen. To check whether our results are robust to different values of $\overline{C}$,

Table 9
Robustness check by choosing different $\overline{C}$.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables:	*ln(AQI)*	*ln(AQI)*	*ln(AQI)*	*ln(AQI)*	*ln(AQI)*	*ln(AQI)*
$I(event_{pt} = 1)$	−0.386**	−0.382**	−0.348**	−0.291*	−0.331*	−0.464**
	(0.15)	(0.15)	(0.16)	(0.17)	(0.19)	(0.23)
Est.	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Date-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,574	28,574	28,574	28,574	28,574	28,574
$\overline{C}$	5	10	30	50	80	100

Notes: Standard errors are in parentheses and clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Weather controls include daily temperature, its square, humidity, and precipitation. $\overline{C}$ refers to the critical value in identifying a prefecture as an epidemic area.

Table 10
Results of the new $\overline{C}$ which depends on the newly-added confirmed cases.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Results in the first stage						
Dependent variables: $I(event_{pt} = 1)$						
$\widehat{M}_{pt,3}$	0.00483***					
	(0.00)					
$\widehat{M}_{pt,6}$		0.00699***				
		(0.00)				
$\widehat{M}_{pt,10}$			0.00960***			
			(0.00)			
$\widehat{M}_{pt,15}$				0.0141***		
				(0.00)		
$\widehat{M}_{pt,25}$					0.0244***	
					(0.00)	
$\widehat{M}_{pt,30}$						0.0399***
						(0.00)
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Date-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.680	0.677	0.674	0.675	0.674	0.675
F-value	38.67	27.41	17.82	21.47	27.04	36.68
Observations	28,574	28,574	28,574	28,574	28,574	28,574
Panel B: Results for *AQI*, *PM₁₀* and *PM₂.₅* in the second stage						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables:	*ln(AQI)*	*ln(AQI)*	$ln(PM_{10})$	$ln(PM_{10})$	$ln(PM_{2.5})$	$ln(PM_{2.5})$
$I(event_{pt} = 1)$	−0.109***	−0.429***	−0.109***	−0.429***	−0.116***	−0.329**
	(0.00)	(0.16)	(0.00)	(0.14)	(0.00)	(0.15)
ESt.	OLS	2SLS	OLS	2SLS	OLS	2SLS
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Date-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,574	28,574	28,574	28,574	28,574	28,574

Notes: Standard errors are in parentheses and clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Weather controls include daily temperature, its square, humidity, and precipitation. $\widehat{M}_{pt,\overline{C}}$ refers to the threat of COVID-19 of prefecture p at day t with $\overline{C} \in \{3, 6, 10, 15, 25, 30\}$, which is measured by the newly-added confirmed cases.

we use all the possible values suggested in the main text, from 5 to 100, to implement our diff-in-diff with 2SLS framework. Table 9 reports the results. Our results suggest that our estimates do not vary too much for different values of $\overline{C}$.

6.4.2.5. $\overline{C}$ depends on the newly-added confirmed cases instead of accumulative cases. In the main results, we identify a prefecture *p'* to be an epidemic area at time *t* if its accumulative number of confirmed cases is higher than a certain threshold $\overline{C}$. In order to check the robustness of the empirical findings, we turn to use the newly-added confirmed cases to measure the risk of a prefecture. Since the average newly-added confirmed cases on the day the lockdown starts is around 3. We chose several values, namely 3, 6, 10, 15, 25, and 30, for new $\overline{C}$ to run the first stage. And we also show the results for the second stage estimation with $\overline{C} = 3$ in Table 10. The results are robust not only in the first stage but also in the second stage.

Table 11
The impact of a prefecture's lockdown on the environment (include Hubei).

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Results in the first stage						
Dependent variables: $I(event_{pt} = 1)$						
$\widehat{M}_{pt,5}$	0.00190***					
	(0.00)					
$\widehat{M}_{pt,10}$		0.00200***				
		(0.00)				
$\widehat{M}_{pt,30}$			0.00230***			
			(0.00)			
$\widehat{M}_{pt,50}$				0.00283***		
				(0.00)		
$\widehat{M}_{pt,80}$					0.00347***	
					(0.00)	
$\widehat{M}_{pt,100}$						0.00409***
						(0.00)
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Date-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.691	0.69	0.687	0.686	0.685	0.684
F-value	51.93	53.43	45.15	40.72	34.83	24.65
Observations	29,484	29,484	29,484	29,484	29,484	29,484
Panel B: Results for *AQI*, *PM10* and *PM2.5* in the second stage						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables:	*ln(AQI)*	*ln(AQI)*	$ln(PM_{10})$	$ln(PM_{10})$	$ln(PM_{2.5})$	$ln(PM_{2.5})$
$I(event_{pt} = 1)$	−0.109***	−0.441***	−0.109***	−0.447***	−0.116***	−0.349**
	(0.00)	(0.15)	(0.00)	(0.14)	(0.00)	(0.15)
ESt.	OLS	2SLS	OLS	2SLS	OLS	2SLS
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Date-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29,484	29,484	29,484	29,484	29,484	29,484

Notes: Standard errors are in parentheses and clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Weather controls include daily temperature, its square, humidity, and precipitation. $\widehat{M}_{pt,\overline{C}}$ refers to the threat of COVID-19 of prefecture p at day t with $\overline{C} \in \{5, 10, 30, 50, 80, 100\}$. We choose 30 for the value of $\overline{C}$ in the second stage.

Table 12
Robustness check for other air pollutant.

	(1)	(2)	(3)	(4)
Dependent variables:	$ln(SO_2)$	$ln(NO_2)$	$ln(CO)$	$ln(O_3)$
$I(event_{pt} = 1)$	−0.468***	−0.339**	−0.191*	0.202*
	(0.14)	(0.13)	(0.10)	(0.12)
Est.	2SLS	2SLS	2SLS	2SLS
Weather controls	Yes	Yes	Yes	Yes
Prefecture-fixed effects	Yes	Yes	Yes	Yes
Date-fixed effects	Yes	Yes	Yes	Yes
Observations	28,574	28,574	28,574	28,574

Notes: Standard errors are in parentheses and clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All the dependent variables are the log values.

6.4.2.6. We also include the samples of Hubei province. In the main results, we eliminated the samples of Hubei province because it is the epicenter of COVID-19, and the preventive and control measures of Hubei might be fundamentally different from which of other regions. Therefore we're concerned about that the samples of Hubei may form the interference to our estimates. But the lockdown of Hubei province seems to be a more exogenous shock to identify the impact on air pollution. So we provide the related regression results which include the samples of Hubei province in Table 11. These results are close to the main results when we excluded the samples of Hubei province.

6.4.2.7. We also test the results for other air-quality outcome measures. In the baseline regressions, we focus on the impacts of the lockdown on the main indicators of air quality. In order to test whether the results are robust to other air pollutant, we adopt the same method to investigate the effect of lockdown on sulfur dioxide (SO_2), nitrogen dioxide (NO_2), carbon monoxide (CO) and ozone (O_3).

Table 13
The results of spatial dependence.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables:	$ln(AQI)$	$ln(PM_{10})$	$ln(PM_{2.5})$	$ln(AQI)$	$ln(PM_{10})$	$ln(PM_{2.5})$
$I(event_{pt} = 1)$	−0.390**	−0.301***	−0.377**	−0.96**	−0.80**	−0.97**
	(0.15)	(0.12)	(0.16)	(0.37)	(0.33)	(0.39)
$I(event_{p't} = 1)$	−0.32***	−0.36***	−0.21***			
	(0.06)	(0.06)	(0.06)			
Est.	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Date-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,574	28,574	28,574	8526	8526	8526

Notes: Standard errors are in parentheses and clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Weather controls include daily temperature, its square, humidity, and precipitation. $I(event_{p't} = 1) = 1$ if a prefecture p's nearby prefecture undertook a lockdown at day t. Otherwise, $I(event_{p't} = 1) = 0$.

Table 14
Robustness check about the prefecture's exposure to the COVID-19 risk.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variables:	$ln(AQI)$	$ln(PM_{10})$	$ln(PM_{2.5})$	$ln(AQI)$	$ln(PM_{10})$	$ln(PM_{2.5})$	$ln(AQI)$	$ln(PM_{10})$	$ln(PM_{2.5})$
$I(event_{pt} = 1)$	−0.522**	−0.412**	−0.501**	−0.297**	−0.238**	−0.268**	−0.103***	−0.101***	−0.117***
	(0.20)	(0.17)	(0.21)	(0.12)	(0.09)	(0.13)	(0.00)	(0.00)	(0.00)
$ln(M_{p,\ t})$							−0.000**	−0.000***	−0.000
							(0.00)	(0.00)	(0.00)
Est.	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	OLS	OLS	OLS
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,574	28,574	28,574	28,574	28,574	28,574	28,574	28,574	28,574

Notes: Standard errors are in parentheses and clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Weather controls include daily temperature, its square, humidity, and precipitation. $ln(M_{p,\ t})$ represents the log value of total population inflow of prefecture p at day t.

The results are shown in Table 12. We find that lockdown measure reduces all the pollutants except for O3. This may be caused by the significant reduction of $PM_{2.5}$ and NO_2, which could inhibit the chemical formation of ozone.

6.4.2.8. Test the spatial dependence. Although we have discussed the exclusion restriction for the instrument variable, there is still spatial dimension that cannot be ignored. Suppose the pollutants can reach the nearby prefecture in a few hours, it may become a possible channel through which $\widehat{M}_{pt}$ is correlated with air quality in p. So we hope to test the possible correlation. First, we control for a dummy which equal to 1 when a nearby prefecture adopts lockdown measures, the results of which are shown in columns (1–3) of Table 13. Second, we eliminate the samples whose neighbor adopts the lockdown measures to run the related regression, which can be seen from columns (4–6) of Table 13. Compare the results of Table 13 with the baseline results, we find that we might underestimated the effect of lockdown on air pollution without considering the spatial dependence.

6.4.2.9. Some questions about the prefecture's exposure to the COVID-19 risk. In our baseline model, for excluding the impact of the Spring Festival travel rush on the instrument, we only used the average bilateral flow of population between January 1 and January 9, 2020 to capture the potential threat of COVID-19. As days go by, this prefecture's exposure to the risk from prefecture p' keeps rising no matter prefecture p' has locked down or not. To solve this problem, we try to use the average population flow of longer time to predict the prefecture's exposure to the COVID-19 risk in consideration of decreasing flow after the breakout of COVID-19. The columns (1–3) of Table 14 shows that when we use the average bilateral flow of population between January 1 and February 12, 2020 to predict the potential threat of COVID-19, the estimates do not vary too much compared with the baseline results. However, there is still some concern that if a prefecture's connected area p' has confirmed cases over $\overline{C}$, whether prefecture p' has an earlier lockdown or not will affect the prefecture differently (Fang et al. (2020); Qiu, Chen, & Shi (2020)). Thus we adjust our construction of $\widehat{M}_{pt}$ by turning $I\left(Case_{p't'} \geq \overline{C}\right)$ into $I\left(Case_{p't'} \geq \overline{C}\right)I\left(event_{p't} = 0\right)$, which is a dummy variable equal to 1 if the number of confirmed cases of prefecture p' at date t is larger than $\overline{C}$ and the prefecture p' did not undertake lockdown measures at date t. As shown in the columns (4–6) of Table 14, the estimates are smaller than which of baseline results but they are still bigger than estimates of OLS results. Moreover, we also try the OLS regressions controlling for real population inflow from an epidemic area in lag days shown in the columns (7–9) of Table 14. Adding this control variable does not change the estimates too much. The absolute values of estimates are still smaller than which of the 2SLS estimates.

7. Conclusion

This paper studies the effect of government response to COVID-19 on the environment. The high frequency (daily) data allows us to precisely compare changes in environmental quality across different prefectures before and after any prefecture undertook lockdown measures. In particular, we find that (1) a prefecture's lockdown had a substantial and significant clean-up effect on air quality, (2) the effect of the lockdown on the environment may be due to the reduction in manufacturing production, and (3) there are significant differences among the effects of various lockdown measures on air pollution.

To estimate the effects of a lockdown on the environment, we exploit the high frequency of the data to develop a novel identification strategy which helps to predict the behavior of the government. As high frequency data become more available, our approach provides an example of how to make the best use of daily variations to identify the effects of the public events and the government decisions. Although our instrument is limited because it is hard to completely prove the validity of it, it is the most appropriate instrument we can find in the available data.

Declaration of Competing Interest

None.

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Appendix

Table A1
The timing and lockdown measures of the prefectures

Beginning of Lockdown	Prefecture	m_1	m_2	m_3	m_4	m_5	m_6	m_7	m_8	m_9	m_{10}	m_{11}	m_{12}
31 January 2020	Wuzhong	0	0	1	0	0	0	0	0	0	0	0	0
	Yinchuan	0	0	1	0	0	0	0	0	0	0	0	0
2 February 2020	Wenzhou	1	1	1	1	0	1	0	1	0	1	0	1
3 February 2020	Huaian	0	0	0	1	0	0	0	1	0	0	0	0
	Changzhou	1	1	1	1	0	0	0	1	0	0	1	0
	Fuzhou	1	1	0	1	0	1	0	1	1	0	1	1
	Haerbin	1	1	1	0	0	0	0	1	0	0	1	1
	Hangzhou	1	1	0	0	0	1	0	1	1	0	0	0
	Jingdezhen	1	1	1	1	0	1	0	1	1	1	0	1
	Linyi	1	1	0	1	0	1	0	1	0	0	1	1
4 February 2020	Nanjing	1	1	0	1	0	1	1	1	1	0	0	0
	Nantong	1	1	1	1	1	1	0	1	1	0	1	1
	Ningbo	1	0	1	0	0	1	0	1	1	0	1	1
	Xuzhou	1	1	1	0	0	0	1	1	0	0	1	1
	Zhengzhou	1	0	1	0	0	0	0	0	0	1	0	0
	Zhenjiang	1	0	1	1	0	0	1	0	1	1	0	0
	Zhumadian	0	0	1	1	1	0	0	1	1	0	0	0
	Haikou	1	1	0	1	0	1	0	1	0	1	1	0
	Hefei	1	1	0	1	1	1	1	1	0	0	1	1
	Jinan	1	1	0	0	0	0	0	1	0	0	1	0
	Kunming	1	1	0	1	0	1	1	1	0	0	0	0
	Nanchang	1	1	1	1	0	1	0	1	0	1	1	1
	Nanning	0	1	0	1	0	0	0	1	1	0	0	0
	Qingdao	1	1	0	1	1	0	0	1	0	1	1	0
5 February 2020	Rizhao	0	0	0	1	1	0	0	1	0	0	0	0
	Sanya	1	1	0	0	1	1	1	1	1	0	1	1
	Shijiazhuang	1	1	0	0	1	1	0	0	1	0	0	0
	Suqian	1	1	1	1	0	1	0	1	0	0	1	0
	Taian	1	1	0	1	1	1	0	1	0	1	1	1
	Taizhou	1	0	0	1	1	0	1	0	0	0	0	1
	Yancheng	0	0	1	1	0	0	0	0	1	0	0	0
	Yangzhou	1	0	1	1	0	1	1	1	1	0	1	0
	Anshan	1	1	1	1	1	0	0	1	0	1	1	0
6 February 2020	Benxi	1	1	1	1	1	0	0	1	0	1	1	0
	Chaoyang	1	1	1	1	1	0	0	1	0	1	1	0

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Table A1 (*continued*)

Beginning of Lockdown	Prefecture	m_1	m_2	m_3	m_4	m_5	m_6	m_7	m_8	m_9	m_{10}	m_{11}	m_{12}
	Dalian	1	1	1	1	1	0	0	1	0	1	1	0
	Dandong	1	1	1	1	1	0	0	1	0	1	1	0
	Fushun	1	1	1	1	1	0	0	1	0	1	1	0
	Fuxin	1	1	1	1	1	0	0	1	0	1	1	0
	Fuzhou	1	1	1	1	0	1	0	1	0	1	0	1
	Ganzhou	1	1	1	1	0	1	0	1	0	1	0	1
	Huludao	1	1	1	1	1	0	0	1	0	1	1	0
	Jian	1	1	1	1	0	1	0	1	0	1	0	1
	Jilin	1	1	1	1	1	0	0	1	0	1	1	0
	Jinzhou	1	1	1	1	1	0	0	1	0	1	1	0
	Jiujiang	1	1	1	1	0	1	0	1	0	1	0	1
	Liaoyang	1	1	1	1	1	0	0	1	0	1	1	0
	Maanshan	1	1	0	1	0	1	1	1	0	0	0	0
	Maanshan	1	1	0	1	1	1	1	1	0	0	1	1
	Neijiang	0	1	0	1	1	1	0	1	0	0	1	0
	Panjin	1	1	1	1	1	0	0	1	0	1	1	0
	Pingxiang	1	1	1	1	0	1	0	1	0	1	0	1
	Shangrao	1	1	1	1	0	1	0	1	0	1	0	1
	Shenyang	1	1	1	1	1	0	0	1	0	1	1	0
	Suzhou	1	0	1	0	0	1	0	0	1	0	0	0
	Tieling	1	1	1	1	1	0	0	1	0	1	1	0
	Xinyu	1	1	1	1	0	1	0	1	0	1	0	1
	Yaan	1	0	1	0	0	1	0	1	0	0	1	1
	Yichun	1	1	1	1	0	1	0	1	0	1	0	1
	Yingkou	1	1	1	1	1	0	0	1	0	1	1	0
	Yingtan	1	1	1	1	0	1	0	1	0	1	0	1
	Zhuhai	1	0	0	1	0	0	0	1	1	0	0	0
	Anqing	1	1	0	1	1	1	1	1	0	0	1	1
	Bengbu	1	1	0	1	1	1	1	1	0	0	1	1
	Bozhou	1	1	0	1	1	1	1	1	0	0	1	1
	Chengdu	1	1	0	1	0	0	1	1	0	0	0	0
	Chizhou	1	1	0	1	1	1	1	1	0	0	1	1
	Chuzhou	1	1	0	1	1	1	1	1	0	0	1	1
	Fuyang	1	1	0	1	1	1	1	1	0	0	1	1
	Guangyuan	1	1	0	1	1	0	1	1	0	0	1	1
	Guangzhou	1	0	0	1	0	1	0	1	1	1	0	0
	Guiyang	1	1	0	1	1	0	1	1	0	0	0	0
	Huaibei	1	1	0	1	1	1	1	1	0	0	1	1
	Huainan	1	1	0	1	1	1	1	1	0	0	1	1
7 February 2020	Huangshan	1	1	0	1	1	1	1	1	0	0	1	1
	Lanzhou	1	0	0	0	0	1	1	1	0	0	0	0
	Lianyungang	1	0	0	1	1	1	0	1	1	0	1	1
	Luan	1	1	0	1	1	1	1	1	0	0	1	1
	Shenzhen	1	1	1	1	1	1	1	1	1	1	0	0
	Suining	1	1	0	1	0	0	1	1	1	0	1	1
	Suzhou	1	1	0	1	1	1	1	1	0	0	1	1
	Tangshan	1	1	0	1	0	1	0	1	0	0	1	0
	Tianjin	1	0	0	0	0	1	1	1	0	0	0	0
	Tongling	1	1	0	1	1	1	1	1	0	0	1	1
	Wuhu	1	1	0	1	1	1	1	1	0	0	1	1
	Xuancheng	1	1	0	1	1	1	1	1	0	0	1	1
	Zunyi	1	1	1	1	1	1	1	1	0	0	0	1
	Chongqing	1	0	0	0	0	1	1	0	0	0	0	0
8 February 2020	Foshan	1	1	0	1	0	1	0	1	0	0	1	0
	Ziyang	1	1	0	0	0	1	0	1	0	0	1	0
	Baicheng	0	1	0	1	0	1	0	1	0	0	0	0
	Baishan	0	1	0	1	0	1	0	1	0	0	0	0
	Changchun	0	1	0	1	0	1	0	1	0	0	0	0
	Deyang	1	1	1	0	0	1	1	1	1	0	0	0
	Dongguan	1	1	1	1	0	1	0	0	1	0	0	0
	Hanzhong	0	0	1	1	0	0	0	0	0	0	0	0
9 February 2020	Huizhou	1	1	0	1	0	1	0	1	1	0	0	0
	Liaoyuan	0	1	0	1	0	1	0	1	0	0	0	0
	Mianyang	1	1	0	1	0	1	1	1	0	0	0	0
	Siping	0	1	0	1	0	1	0	1	0	0	0	0
	Songyuan	0	1	0	1	0	1	0	1	0	0	0	0
	Tonghua	0	1	0	1	0	1	0	1	0	0	0	0
	Wuxi	1	0	0	1	1	1	0	0	0	0	1	0
10 February 2020	Beijing	1	1	1	1	1	1	1	1	0	0	0	0
	Shanghai	1	0	0	1	1	0	0	0	1	0	0	0

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Table A1 (*continued*)

Beginning of Lockdown	Prefecture	m_1	m_2	m_3	m_4	m_5	m_6	m_7	m_8	m_9	m_{10}	m_{11}	m_{12}
12 February 2020	Alashan	1	1	0	1	1	1	0	1	0	0	1	1
	Baotou	1	1	0	1	1	1	0	1	0	0	1	1
	Bayannaoer	1	1	0	1	1	1	0	1	0	0	1	1
	Chifeng	1	1	0	1	1	1	0	1	0	0	1	1
	Eerduosi	1	1	0	1	1	1	0	1	0	0	1	1
	Huhehaote	1	1	0	1	1	1	0	1	0	0	1	1
	Hulunbeier	1	1	0	1	1	1	0	1	0	0	1	1
	Tongliao	1	1	0	1	1	1	0	1	0	0	1	1
	Wuhai	1	1	0	1	1	1	0	1	0	0	1	1
	Wulanchabu	1	1	0	1	1	1	0	1	0	0	1	1
	Xilinguole	1	1	0	1	1	1	0	1	0	0	1	1
	Xingan	1	1	0	1	1	1	0	1	0	0	1	1

Notes: The number 1 represents that the prefecture adopts the corresponding lockdown measure. This table only shows the heterogenetic lockdown measures across prefectures. So the common measures such as setting up checkpoints, cleaning and disinfecting the community, canceling mass gatherings and so on, are not included in the table. Besides, the 12 prefectures of Hubei are not included in this table because their lockdown measures are much more severe than which of other prefectures. The specific lockdown measures are as follows: 1) Contactless delivery; 2) Communities with confirmed cases may implement closed isolation; 3)All visitors and exotic vehicles are not allowed to enter the community; 4) Travelers from the Epidemic Area Need to be Quarantined for 14 Days upon Arrival to the Prefecture; 5) Close contacts need to be quarantined at assembly sites; 6) Public places not necessary for the lives of residents should be closed; 7) Suspension of non-essential project; 8) Communities should strengthen management of rental housing; 9) Persons Stranded in the Epidemic Area Could not Return; 10) Health QR code or pass shall be used to manage people; 11) Wedding suspended and funeral simplified; 12) Each family (exclude home quarantine families) could only assign one family member to purchase daily supplies every two/three days.

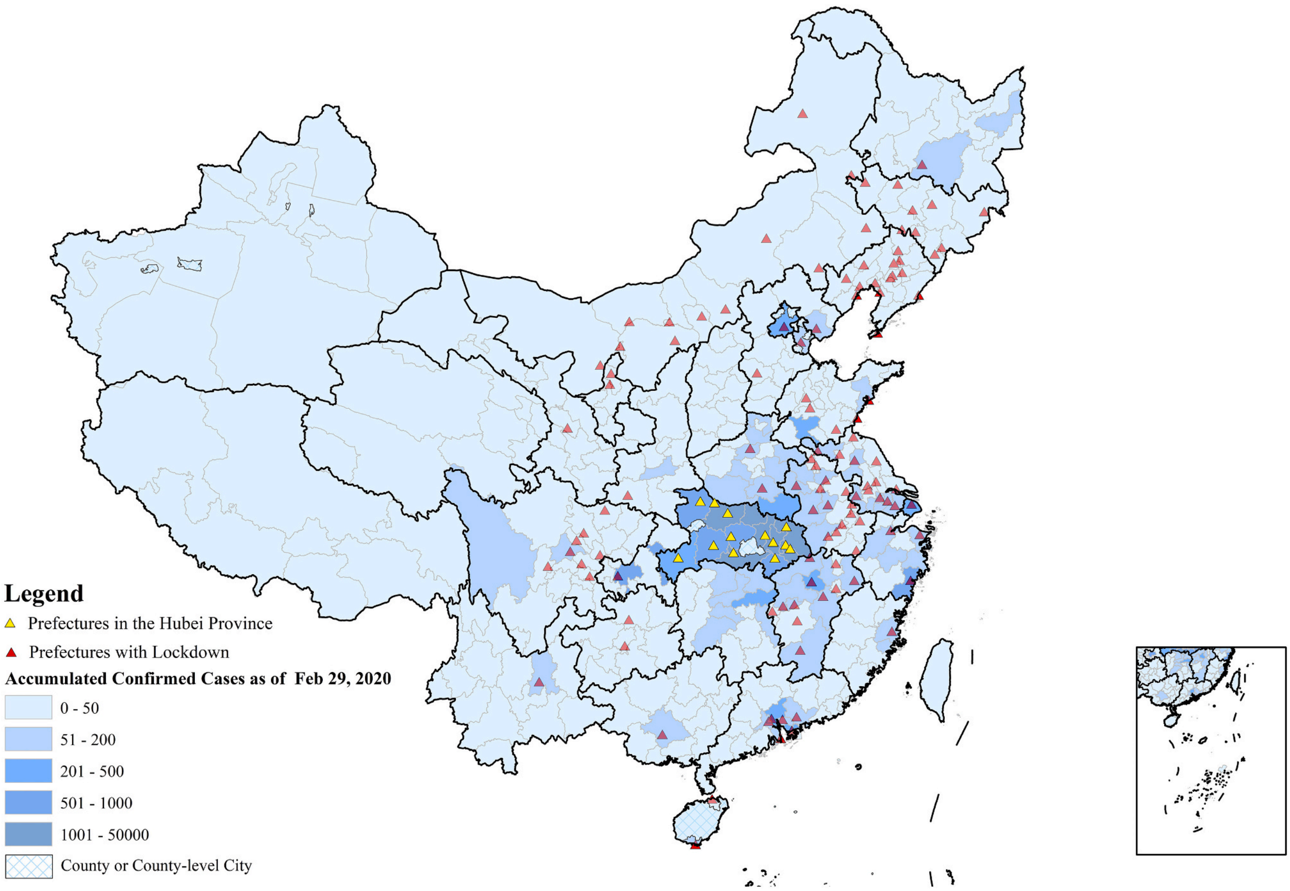

Fig. A1. The Spatial distribution of lockdowns.
Notes: This figure shows us the spatial distribution of lockdown undertook by the prefecture. In the map, the yellow triangles represent prefectures of Hubei Province, the red triangles represent the prefectures with lockdowns, and the different depths of color of the blue reflect the different levels of the number of confirmed COVID-19 Cases as of Feb 29, 2020.

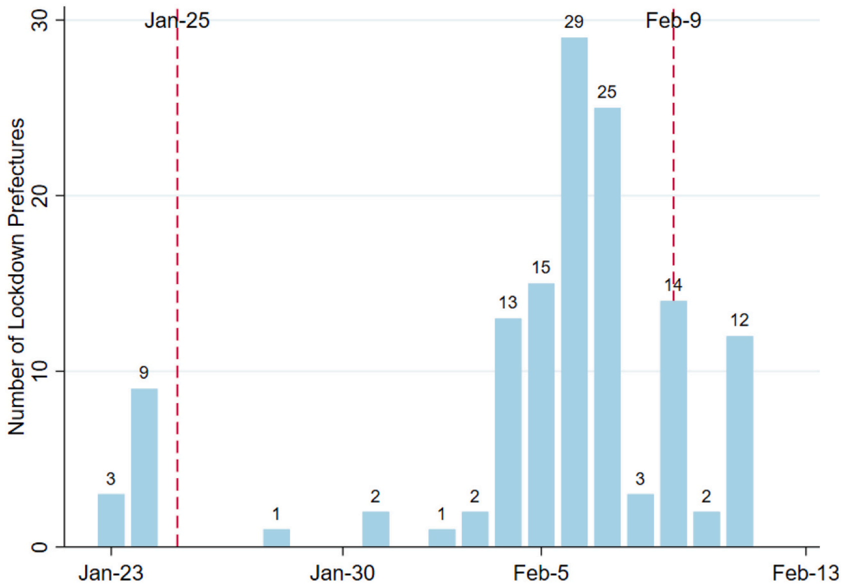

Fig. A2. The timing of the lockdowns.

Notes: This figure shows us the timing of the lockdowns. Between January 23 and January 28, 13 prefectures inside the Hubei province undertook lockdown measures. After January 30, prefectures outside Hubei started to *undertook* lockdowns around February 5th. The red line, which indicates the date January 25, 2020, marked the starting of the Spring Festival Holiday, and the other red line which indicates the date February 9th, marked the end of the Spring Festival.

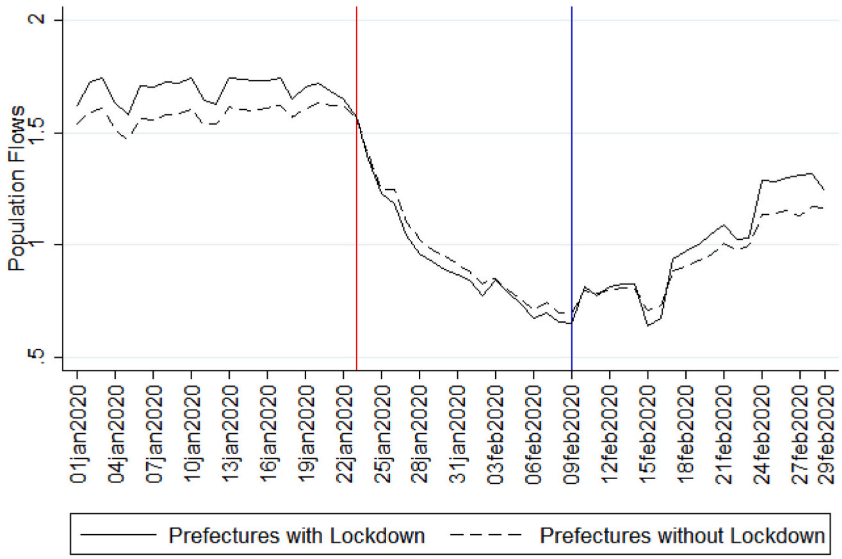

Fig. A3. Average within-prefecture flow.

Notes: This figure shows us the dynamics of the population mobility within the prefecture. We divide the prefectures into two groups: with and without a lockdown measure. The solid line indicates the group of prefectures with lockdown measures and the dash line indicates the group of prefectures without lockdown measures. January 23rd marked the day when Wuhan undertook a lockdown measure, two days before Spring Festival. February 9th marked the end of the Spring Festival.

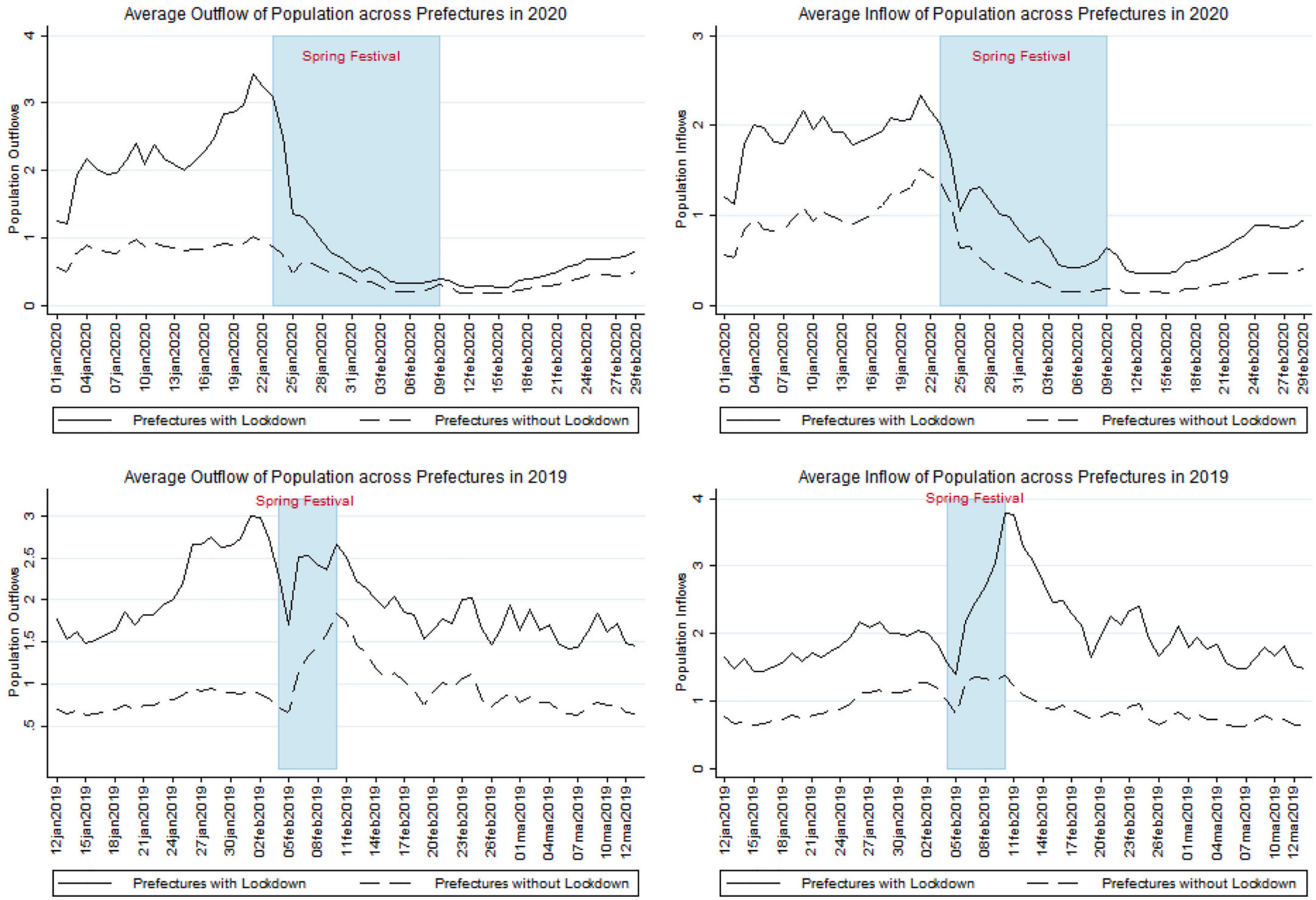

Fig. A4. The dynamics of population flow.

Notes: This figure shows us the dynamics of daily total population outflow and inflow for two different prefecture groups in 2019 and 2020 respectively. The solid line represents the prefectures that received lockdown measures (treatment group). The dash line represents the prefectures without lockdown measures (control group). The prefectures in both the group with and without lockdown measures are time-invariant. If a prefecture received a lockdown measure during our study period, this prefecture would be assigned in the treatment group. The shade area represents the Spring Festival period.

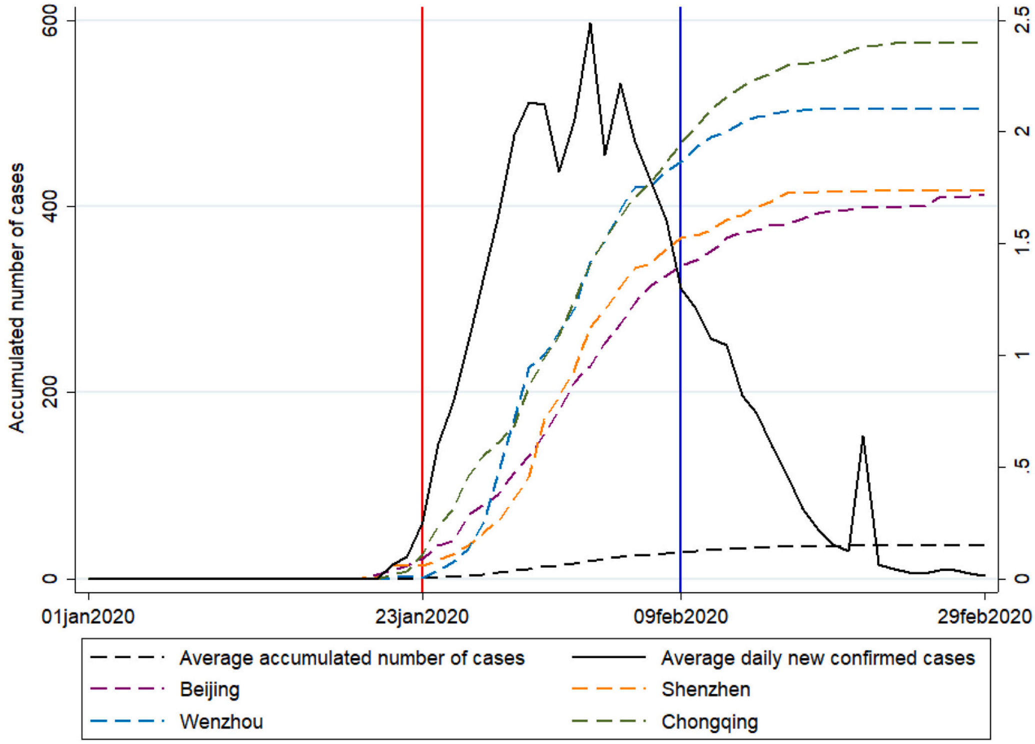

Fig. A5. The dynamics of confirmed cases outside Hubei.

Notes: This figure plots the dynamics of the average accumulated number of infected cases, the average daily new infected cases and the four prefectures with most infected cases outside Hubei. The black solid and dash lines represent the average daily new confirmed cases and the average number of cumulative confirmed cases in China outside Hubei province, respectively. The dash purple, orange, light blue and green lines represent the number of cumulative cases in Beijing, Shenzhen, Wenzhou, and Chongqing respectively.

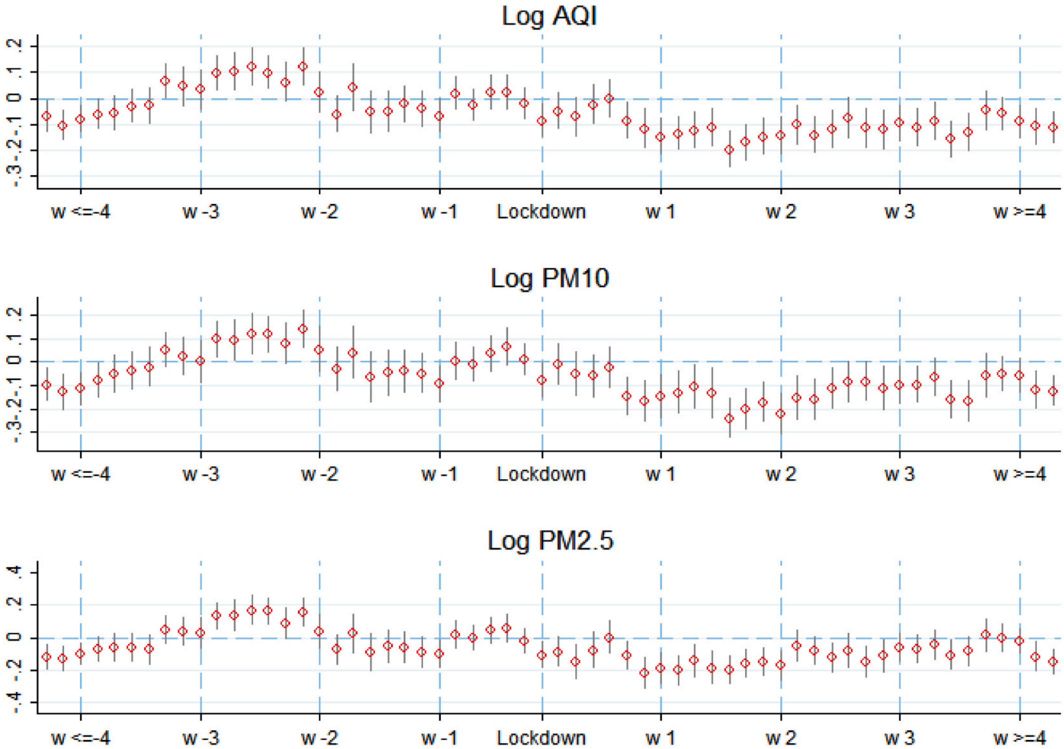

Fig. A6. Event study of lockdown on the air pollution.

Notes: This figure shows the results of the event study for air pollution. The y axis represents the log of AQI, PM10 and PM2.5, and the x axis represents time. w1, w2, and w3 represents the first, second and the third week after the lockdown, respectively. w $\geq$ 4 represents four weeks after lockdown. w-1, w-2, and w-3 represents the first, second and the third week before the lockdown, respectively. w ≤ -4 represents four weeks before lockdown. Our estimates have already controlled for a prefecture's daily precipitation and temperature, which are both time-variant. We also report 90% confidence bound for the daily estimates. We omit the estimates of a day before the lockdown.

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