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The casual effects of COVID-19 lockdown on air quality and short-term health impacts in China

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ABSTRACT

The outbreak of coronavirus (COVID-19) has forced China to lockdown many cities and restrict transportation, industrial, and social activities. This provides a great opportunity to look at the impacts of pandemic quarantine on air quality and premature death due to exposure to air pollution. In this study, we applied the difference-in-differences (DID) model to quantify the casual impacts of COVID-19 lockdown on air quality at 278 cities across China. A widely used exposure-response function was further utilized to estimate the short-term health impacts associated with changes in $PM_{2.5}$ due to lockdown. Results show that lockdown has caused drastic reduction in air pollution level in terms of all criteria pollutants except ozone. On average, concentrations of $PM_{2.5}$, PM_{10}, NO_2, SO_2 and CO are estimated to drop by 14.3 μg/m^3, 22.2 μg/m^3, 17.7 μg/m^3, 2.9 μg/m^3, and 0.18 mg/m^3 as the result of lockdown. Cities with more confirmed cases of COVID-19 are related to stronger responses in air quality, despite that similar lockdown measures were implemented by the local governments. The improvement of air quality caused by COVID-19 lockdown in northern cities is found to be smaller than that of southern cities. Avoided premature death associated with $PM_{2.5}$ exposures over the 278 cities was estimated to be 50.8 thousand. Our results re-emphasize the effectiveness of emission controls on air quality and associated health impacts. The high cost of lockdown, still high level of air pollution during lockdown and smaller effects in northern cities implies that source-specific mitigation policies are needed for continuous and sustainable reduction of air pollution.

1. Introduction

In December 2019, several cases of "unknown viral pneumonia" were first reported in Wuhan, China (WHO, 2020), which was detected and later termed COVID-19 in January 2020 (Cui et al., 2019). By the middle of February 2020, there were around 60,000 confirmed cases within China (DXY, 2020). Around January 24th, 2020, China's provincial governments announced first level (Level I) major public health emergent response in order to reduce the intensity of the epidemic and slow down the increase of number of new cases. During the Level I response phase, all kinds of human activities were greatly reduced. Industries except power plants and certain industries (e.g. iron, medical and pharmaceutical) were strongly affected by the lockdown. Cement production is reported to be 29.5% lower in January and February 2020 than in 2019 (Huang et al., 2021). For non-industrial sectors, national traffic volume is estimated to drop by more than 70% due to restrictions on the transportation sector (Huang et al., 2021; Li et al., 2021; Xinhua News, 2020), which is the dominant contributor of NOx emission reductions during lockdown. Construction sites, restaurants, schools, and almost entire service sectors were suspended proactively or reluctantly. This massive national lockdown has inevitably caused tremendous impacts on all aspects of people's life. Extensive studies have been and continued to be conducted to investigate the impacts brought by COVID-19 on different aspects. For instance, many studies have been focusing on the impacts of COVID-19 on the economy, both microeconomic (i.e. stock market, household consumption, unemployment) (Baker et al., 2020a, 2020b; Ramelli and Wagner, 2020; Baker et al., 2020a,b; Coibion et al., 2020) and macroeconomic (e.g. supply and demand) (Guerrieri et al., 2020; Del Rio-Chanona et al., 2020; Ludvigson et al., 2020). There are also studies looking at the impacts on psychology (e.g. Hamermesh, 2020) due to individual social distancing. The impact of COVID-19 on the natural environment has also been a hot topic. For

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example, Le Quere et al. (2020) quantified the decrease in global CO_2 emissions during forced confinement. A couple of studies look at the relationship between the severity of air pollution and COVID-19 infection (Zhu et al., 2020; Fattorini and Regoli, 2020; Contini and Costabile, 2020; Xu et al., 2020; Hendryx and Luo, 2020; Conticini et al., 2020). Some studies focused on the transmission of COVID-19 via airborne aerosols (Zhang et al., 2020; Wang and Du, 2020).

Meanwhile, regional air pollution has been a major environmental problem in China in the past decades due to urban expansion and industrialization. High concentrations of $PM_{2.5}$ (fine particles with an aerodynamic diameter of less than 2.5 μm) during the winter time and elevated ozone concentrations during the summer time (K. Li et al., 2019) have posed adverse impacts on public health, especially over dense population regions (Song et al., 2017; Maji et al., 2018, 2019). Previous studies have reported a wide range of 0.19–1.60 million/year premature mortality due to $PM_{2.5}$ exposure in China and ambient particulate matter pollution ranks the fourth leading cause of deaths in China (Wang et al., 2013; Lim et al., 2012; Liu et al., 2016; Yang et al., 2013). On the other hand, ground-level ozone is estimated to contribute around 70,000 premature deaths in China due to respiratory and cardiovascular problems (Cohen et al., 2017; Maji et al., 2019). Therefore, the Chinese government has issued series of emission control policies, with the aim to reduce emissions from various sources, including industry, mobile vehicle exhausts, coal power plants, and residential activities (Karplus et al., 2018; Silver et al., 2018; State Council of the People's Republic of China, 2013; The state council, 2018; Zhang et al., 2019). As a consequence, the concentrations of SO_2 and $PM_{2.5}$ have decreased substantially (Zhang et al., 2019; Ministry of Ecology and Environment of China, 2019). The ozone concentration, on the other hand, exhibits an increasing trend (Lu et al., 2018) due to less control of the VOCs (volatile organic compounds) emissions (P. Wang et al., 2019; Yu et al., 2019), and also related to the reduction in $PM_{2.5}$ concentrations, which could indirectly affect ozone concentrations by altering the photolysis rates and heterogeneous reactions (Li et al., 2018, 2019, 2020; Xing et al., 2017). The annual average $PM_{2.5}$ concentration of mainland China was 39.1 μg/m^3 in 2019 (IQAir, 2019), which ranks as the 11th most polluted country and is still much higher than the standard (10 μg/m^3) recommended by the World Health Organization (WHO). Therefore, it remains an important task to continuously improve the air quality in China with the objective of controlling $PM_{2.5}$ and ozone simultaneously.

No doubt that the outbreak of COVID-19 is a tragedy. Nevertheless, it represents a unique opportunity to look at the response of air quality to short-term but substantial changes in anthropogenic emissions. A number of recent studies thus have been published that discussed the changes of air quality in China as well as other parts of the world due to COVID-19 (e.g. Mahato et al., 2020; Bauwens et al., 2020; Shi et al., 2020; Huang et al., 2020; Le et al., 2020; Chang et al., 2020; Sharma et al., 2020; Nakada et al., 2020; Rodríguez-Urrego and Rodríguez-Urrego, 2020; Sarfraz et al., 2020; etc.). For studies focusing China, some performed extensive analysis of ground observed and/or satellite data before and during the COVID-19 lockdown period; some also conducted air quality simulations to separate the influences of meteorological variations and emission changes on observed changes in air quality (e.g. Zhao et al., 2020; Wang et al., 2020; Huang et al., 2020; Li et al., 2020). To give a few examples, Wang et al. (2020) applied an integrated meteorology and air quality model to show that unfavorable meteorology overwhelmed the benefits of emission reductions, thus leading to severe air pollution events during lockdown. Based on comprehensive measurements, Huang et al. (2020) found that reductions of primary emissions were partially offset by enhanced secondary pollution during lockdown. Li et al. (2020) focused on the changes of air quality over the Yangtze River Delta region based on analysis of observed data as well as model simulations. All these studies lead to a similar observation that COVID-19 has resulted in substantial reductions in terms of NO_2 and $PM_{2.5}$, with the reductions of the latter partially offset by un-favored meteorological conditions or enhanced secondary formation. However, a major uncertainty of some of these studies is related to the difficulty of accurately estimating emission reductions during COVID-19 lockdown, which would result in subsequent uncertainties associated with the modeling results. The influence of inter-annual variations of meteorology is another factor that makes the story more complicated.

In this study, we utilized a completely different method to quantify the casual effects of COVID-19 lockdown on air quality in China and associated short-term health impact. To answer the first half of the question, the differences-in-differences (DID) method was applied over observed concentrations of criteria pollutants for 278 cities across China. The key challenge in evaluating the causal effects of Level I response on air quality is to avoid attributing the Level I response to the effects of other factors, for example, changes in meteorological conditions, social influences over the same time period. One of the standard methods to control these other effects in statistics and economics is the DID analysis. The DID analysis avoids the need to specify any of the other possible meteorological or social influences by comparing the changes in air quality for cities under Level I response to the change for cities that are not under Level I response but otherwise subject to these similar other influences. The difference between these two differences (i.e. differences-in-differences) measures only the effects of the Level I response policy. The DID method outperforms the other commonly used regression methods (e.g. ordinary least square and time series regression) as it mitigates the effects of extraneous factors and selection bias by comparing the difference between treatment group and control group. DID has been used to evaluate the causal impacts of government policies and exogenous natural shocks (Currie et al., 2009; Beck, Levine and Levkov, 2010; Fu and Gu, 2017; Qiu and He, 2017; Wan et al., 2019). It is also becoming prevalence in air pollution field, such as Auffhammer & Kellogg (2011), He et al. (2020), Son et al. (2020) and Navinya et al. (2020). More details with respect to the DID model can be found in Angrist and Pischke (2008).

Application of the DID method allows us to control the unobserved time and city invariant factors or the inter-annual variations associated with meteorological conditions. Therefore, our results represent the causal impact of COVID-19 lockdown on observed changes in the air quality. In this study, we first estimate the changes of air quality due to Level I response policy. The level of changes in air pollution associated with the severity of COVID-19 outbreak was then investigated and different effects of lockdown policy on regional air quality improvement for northern and southern cities were contrasted and discussed. Lastly, the short-term health impacts related to COVID-19 lockdown was quantified as premature mortality due to exposure to ambient $PM_{2.5}$ base on a widely-used exposure-response function.

2. Methodology

2.1. Data

The two data sets used in this study include the observed daily air quality data from January 1st, 2019 to March 31st, 2020 and the cumulated number of COVID-19 confirmed cases for 278 cities in China from January 1st, 2020 to March 28th, 2020. The city-level air quality data includes daily averaged concentrations of six criteria pollutants: $PM_{2.5}$, PM_{10} (particles with an aerodynamic diameter of less than 10 μm), ozone (O_3), sulfur dioxide (SO_2), nitrogen dioxide (NO_2) and carbon monoxide (CO), which are obtained from China Environmental Monitoring Service. The number of COVID-19 confirmed cases is obtained from the DingXiang Doctor pandemic real-time report (DXY, 2020), which tracks the real-time confirmed cases all over the country.

2.2. The difference-in-differences (DID) model

In the basic specification, we estimate how much city-level air quality has improved during the lockdown period. In this model, the cities in Level I response are the treatment group and the cities not in Level I response are the control group. We define the treatment period from the day the Level I response was announced to the day the response level was lifted (i.e. changed to Level II response). Different provinces and cities have different announce time for Level I response or lockdown. Most provinces announced the first-level response on January 24th, 2020 (Global Times, 2020). Guangdong, Jiangsu and Hunan provinces are the earliest provinces to announce a Level I response on January 23rd while the last province Tibet announced Level I response on January 29th. As for Wuhan, the earliest and the most severely affected city, a city-level shut down was announced on January 23rd and the Level I response was announced at January 24th. We take January 23rd as the starting date of treatment for Wuhan.

Besides the treatment and control group setting, we include city fixed effects to control the unobserved and time-unvarying city attributes that affect air quality, month fixed effects to control the unobserved confounding trends that affect air quality and the weekend and holiday fixed effect to control the expected drop in pollution during weekends and holidays:

$$y_{it} = \alpha_0 + \alpha_1 T + Weekend + Holiday + \delta_i + \delta_t + \varepsilon_{it} \tag{1}$$

where the outcome variable y_{it} is one of the air pollution indexes in city i on day t, including $PM_{2.5}$, PM_{10}, O_3, SO_2, NO_2 or CO. α_0 is the constant term and α_1 is the key estimates which measures the air quality improvement during lockdown compared with no lockdown. T is a dummy variable set to 1 if city i was during Level I response period on day t. *Weekend* and *Holiday* are 1 if t is a weekend or a national holiday. δ_i and δ_t are city fixed effect and month fixed effect, respectively. ε_{it} is the error term. We are mostly interested in coefficients α_1 in this model as α_1 captures the average lockdown effect on air quality for all cities.

To investigate the heterogeneous impacts on Level I response on air quality for cities with different severity of COVID-19 outbreak, our second analysis uses a panel data difference-in-differences model to estimate the level of changes in air pollution associated with the severity of COVID-19 outbreak, which is illustrated by Fig. 1. Here the total number of confirmed cases by March 28th is used to classify the treatment and control group. We divided the 278 cities into 3 groups (Table S1): total number of confirmed cases less than 10 (161 cities), between 10 and 99 (181 cities), and above 100 (53 cities). The averaged confirmed cases the three groups are 4 (95% CI: 1–9), 33 (95% CI: 10–93), and 1594 (95% CI: 100–50006), respectively. The group of cities with less than 10 cases is treated as the control group. As shown in Fig. 2, cities with total number of confirmed cases over 100 are either

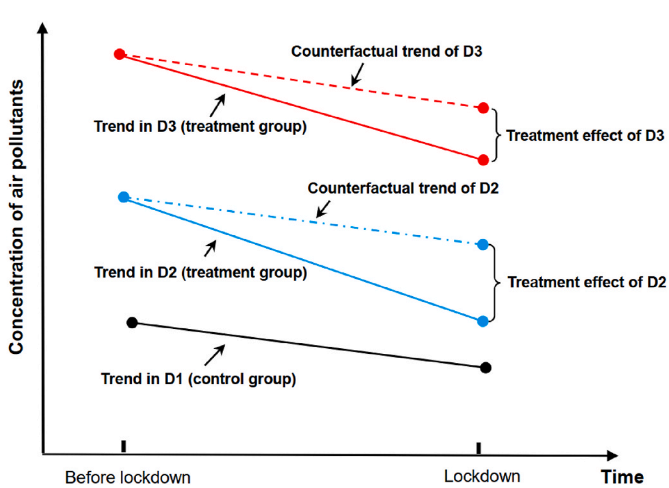

Fig. 1. Causal effects in the difference-in-differences model.

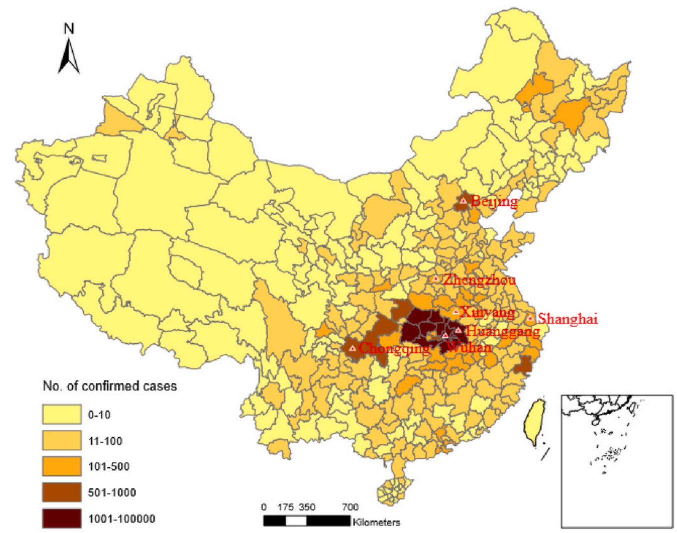

Fig. 2. Number of confirmed cases by city in China as of March 28th, 2020

densely populated cities (e.g. Beijing (576), Shanghai (492), Chongqing (579)), cities in Hubei province (e.g. Wuhan (50,006), Huanggang (4,584)), or cities near Hubei province (e.g. Xinyang (274) and Zhengzhou (158) in Henan province). We use the following model specification:

$$y_{it} = \beta_0 + \beta_1 T + \beta_2 D_2 {}^* T + \beta_3 D_3 {}^* T + Weekend + Holiday + \delta_i + \delta_t + \varepsilon_{it} \tag{2}$$

where D_1, D_2, D_3 are dummy variables which is equal to 1 if the cumulated confirmed count of city i falls the corresponding group.[1] β_0 is the constant term. β_1 is the causal effects of Level I response on air quality for cities in control group (D1). β_2 and β_3 measure the changes of air quality due to lockdown for group 2 (D2) and group 3 (D3) compared with the control group, respectively. Similarly, the DID setup avoids the need to specify any of the other possible influences by comparing the change in air quality for cities in these three groups with different outbreak severity but otherwise subject to these same other influences. The difference between these differences in air quality measures only the effects of the Level I response policy and the severity of outbreak in those cities.

To test the robustness of our results, we tried with three options in terms of the control period (as shown in Fig. 3). The first control period starts from November 2019 to the end of Level I response period (Scenario 1). For this scenario, both the treatment and control periods are winter time. For the second option, we extend the start of the control period to January 2019 (Scenario 2) and for the last option we further extend the end of the control period to March 31st 2020 (Scenario 3).

We are mostly interested in the coefficients of the two interaction terms, β_2 and β_3, which represent the effects of COVID-19 lockdown on air pollution for different groups of cities compared with the cities with least confirmed cases, by controlling for various time and city impacting factors. We cluster the standard errors at the city level for both models. Table S3 presents the summary of statistical results of the key variables used in the DID model.

A third analysis was performed to investigate the heterogeneous impacts of Level I response on cities with or without the coal-based centralized heating systems. Winter heating in the northern China is usually associated with heavy air pollution due to massive consumption of coal. The massive coal consumption could partly offset the

[1] D1, D2 and D3 are multicollinear and perfectly correlated. Hence, we follow the tradition in econometrics to drop D1 in equation (2).

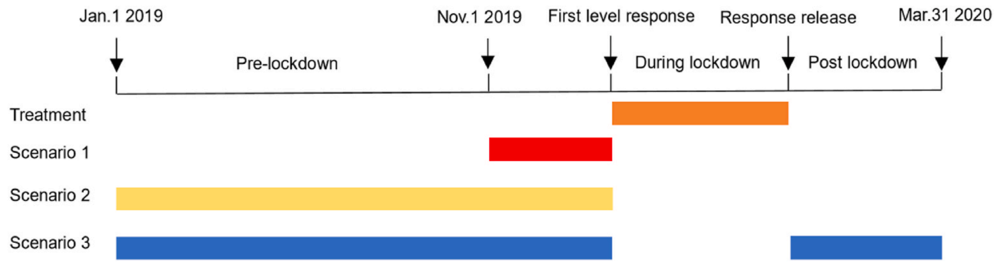

Fig. 3. Settings of the treatment period and the control periods.

improvement of air quality caused by Level I response. To test whether the Level I response policy has different effects on the regional air quality improvement for northern and southern cities in China, we use the usual demarcation line of the Qinling Mountains to the Huaihe River to divide those cities into two groups (northern and southern), as shown in Figure S1. Our third DID model (as shown in Eq. (3)) estimates the level of changes in air pollution associated with the lockdown for northern and southern cities, respectively.

$$y_{it} = \gamma_0 + \gamma_1 T + Weekend + Holiday + \delta_i + \delta_t + \varepsilon_{it} \tag{3}$$

where γ_1 measures the changes of air quality during lockdown compared with no lockdown for cities locate in different regions. The estimation results for this analysis are presented in Table 2.

Two recent studies use similar difference-in-difference approach to study the impacts of government measures during the COVID-19 outbreak on air quality in China. Chen et al. (2020) compared the changes in air quality in 2020 versus 2016–2019 during the quarantine period (Feb 10 to March 14) with those changes in the before-quarantine period (Jan 5 to Jan 20). He et al. (2020) defined some local government measures as lockdown policies and compared the air quality changes for lockdown cities with the changes for cities without lockdown policies in 2020. Our paper presents two analyses: the first one is similar to Chen et al. (2020), but our treatment is Level I Response policies, which is more clearly defined than their quarantine period; the second analysis compares the air quality changes between cities with different level of confirmed cases. In our view, almost all Chinese cities were in some degree of lockdown during the Level I Response period. However, the impacts of government policies on people's behaviors and air quality are quite different and the difference depends on how the cities are affected by the COVID-19 outbreak. The number of confirmed cases is a better measure of how the cities were affected by this outbreak. In short, Chen et al. (2020) did not account for the heterogeneity of the impacts of the quarantine measures. He et al. (2020) used a different treatment than ours and did not discuss its mortality implications. In addition, we conduct parallel trend test and robustness checks. Based on the empirical results, we also conduct the counterfactual analysis to calculate $PM_{2.5}$ related premature deaths on the national level.

2.3. Parallel trend test

One key assumption of the DID model is the parallel trend assumption which means dependent variable of cities in different groups have parallel trends before treatment was implemented, hence the differential effects of these groups are caused by the treatment. In the first model, as provinces announced the Level I response in a short period of time, it is hard to test the parallel trend and we focus on this test for the second model. Following Beck, Levine and Levkov (2010), we test the parallel trend by examining the dynamics of the relation between lockdown and air quality by including a series of dummy variables in the DID regression to trace out the day-by-day effects of lockdown on $PM_{2.5}$ and PM_{10}, which are the most concerned air quality indicators in the winter. If these day-by-day effects are insignificantly different from zero for all days before lockdown, then the air quality of these cities in different group exhibit parallel trends.

To examine the dynamics of air quality and lockdown, we re-group the cities into two groups: control group is group 1, and new treatment group is group 2 and group 3. We run the following regressions:

$$y_{it} = \beta_0 + \beta_1 {*} T + \beta_2 {*} D\_T_{it}^{-6} + \beta_3 {*} D\_T_{it}^{-5} + \cdots + \beta_9 {*} D\_T_{it}^{+2} + Weekend + Holiday + \delta_i + \delta_t + \varepsilon_{it} \tag{3a}$$

where the lockdown interaction dummy variables, D_T^{-j} equals one for cities in the treatment group in the *j*th day before Level I response announcement, and D_T^{+j} equals one for cities in the treatment group in the *j*th day after Level I response announcement, otherwise they equal to zero. We exclude the day of announcement, thus estimating the dynamic effect of lockdown on $PM_{2.5}$ and PM_{10} relative to the day of announcement.

2.4. Premature mortality due to short-term $PM_{2.5}$ exposure

In this study, we attempted to estimate the short-term health impacts by calculating the premature mortality due to $PM_{2.5}$ exposures. A widely-used exposure-response function (Fang et al., 2016; Gao et al., 2016) is used to estimate the premature mortality for each group:

$$Y = \sum_k P \times \left(1 - e^{-\beta_k (C - C_0)}\right) \times R_k \tag{4}$$

where Y is the total number of premature deaths of each group caused by ambient $PM_{2.5}$ exposures due to cardiovascular disease (stroke, ischemic heart disease (IHD)) and respiratory disease (chronic obstructive pulmonary disease (COPD), lung cancer (LC) for adults (≥25 years), and acute lower respiratory infection (ALRI) for infants (<5 years)). β is the cause-specific exposure-response coefficients and the values are obtained from a meta-analysis study (Lu et al., 2015). The baseline incidence rate (R) at provincial level is obtained from the Tabulation on the 2010 Population Census of the People's Republic of China (National Bureau of Statistics and Census Office of the State Council, 2010). The contribution of each disease to total mortality is based on the national estimates from the Global Burden of Diseases (GBD) project of Institute for Health Metrics and Evaluation (IHME) and Health Effects Institute (HEI) for year 2017. P is the exposed population. The exposed $PM_{2.5}$ concentration (C) used in Eq. (4) is the population-weighted $PM_{2.5}$ concentration over all cities or cities within a DID group. The threshold concentration (C_0) of 25 μg/m^3 recommended by the WHO air quality guidelines (WHO, 2015) is used in this study. More details with respect the parameters used in Eq. (4) can be found in our previous study (Huang et al., 2020). We first estimate the premature mortality due to $PM_{2.5}$ exposures during the lockdown period based on the population-weighted observed $PM_{2.5}$ concentration. Then this concentration is adjusted based on the T value from the DID model to represent average $PM_{2.5}$ concentration assuming no lockdown occurred. The differences of the premature mortality estimated based on these 2 p.m.$_{2.5}$ concentrations (observed and adjusted) are considered as the total avoided premature death due to lockdown.

Health impact due to ozone exposure is ignored since the study period is outside the typical ozone season (Wang et al., 2017). However, a most recent study by Li et al. (2021) highlights the spreading of ozone pollution into winter-spring over the North China Plain due to reduced NOx emissions and the ozone health burden is found to be more pronounced in the cool season (Huang et al., 2018; Yin et al., 2017). Thus, the health impact associated with elevated ozone concentration during the lockdown period may partially offset the health benefits associated with the reduced $PM_{2.5}$ concentration.

3. Results and discussions

3.1. Analysis of observed concentrations for different groups

Fig. 4 compares the national averaged concentration of criteria air pollutants before (January 9th – January 23rd, 2020) and during (January 24th to February 24th, 2020) Level I response. All pollutants except ozone decreased by 19.4% (SO_2, Std. Dev.: 16.27%) ~49.8% (NO_2, Std. Dev.: 9.12%). The concentration of $PM_{2.5}$ decreased by 34.9% (Std. Dev.: 19.80%) on average; maximum relative decrease of $PM_{2.5}$ was observed in Suihua (Heilongjiang province) by 55.6% and maximum absolute decrease of $PM_{2.5}$ was observed in Harbin (Heilongjiang province) by 91.0 μg/m^3. Ozone based concentration indices increased by 44.2% (Std. Dev.: 42.76%) for 1-hr maximum ozone (O_{31}) and 30.3% (Std. Dev.: 33.73%) for maximum 8-hr average ozone (O_{38}). A slight downward trend of city-level $PM_{2.5}$ concentration during Level I response was observed with increased number of accumulated confirmed cases (Figure S2).

We also compare the change of air pollutant concentrations for group 1 (*D1*), group 2 (*D2*) and group 3 (*D3*) (data not shown). Similar trend was observed for all three groups with all pollutants except ozone exhibit decreasing trend while ozone increased during Level I response. $PM_{2.5}$ decreased by 28.9% (*D1*, Std. Dev.: 19.18%), 36.5% (*D2*, Std. Dev.: 20.58%) and 38.3% (*D3*, Std. Dev.: 17.59%) and the corresponding O_{31} increased by 36.1% (Std. Dev.: 39.18%), 46.2% (Std. Dev.: 43.56%) and 51.6% (Std. Dev.: 39.03%). It seems that stronger response of air quality was observed for cities with more confirmed cases.

However, the changes of air pollutant concentrations are associated with many controlling factors, for example, variations in meteorological conditions, intrinsic seasonal variability, emissions reduction due to COVID-19 lockdown, etc. The application of DID model allow us to estimate the air quality improvement effect of lockdown without observing these factors, which is presented below.

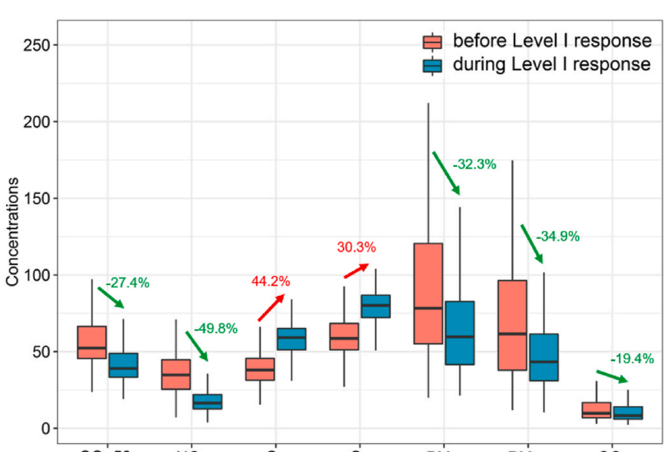

Fig. 4. Concentration of criteria air pollutants over 278 cities before and during Level I response (Note: the unit of CO is mg/m^3; the unit of other pollutants is μg/m^3).

3.2. Results from the DID model

Table 1 presents the estimates of Model (1) and Model (2) for the samples from November 1st, 2019 to the release of Level I response (i.e. Scenario 1 in Fig. 3). Recall that in Model (1) we measured the average impacts of lockdown on air quality while in Model (2) we quantified the level of air quality improvements associated with the severity of the COVID-19. The dependent variables are the eight air pollution indices. All control variables are included but we only report the coefficients of T (1 if during lockdown, 0 otherwise) and two interaction terms due to limited space. These estimates are robust for all indices. On average, concentrations of $PM_{2.5}$, PM_{10}, NO_2, SO_2 and CO dropped by 14.3 μg/m^3 (by 25.37%, Standard Error: 2.09), 22.2 μg/m^3 (25.68%, Standard Error: 2.33), 17.7 μg/m^3 (45.82%, Standard Error: 0.83), 2.9 μg/m^3 (20.51%, Standard Error: 0.37), and 0.18 mg/m^3 (18.20%, Standard Error: 0.02) due to lockdown, respectively. Bear in mind that these estimated changes are caused by the implementation of Level I response as they are the difference between treatment group and control group and many other influential factors are controlled. In contrast, the two O_3-based indices increased by 15.5 μg/m^3 (39.93%, Standard Error: 1.04) and 17.0 μg/m^3 (27.31%, Standard Error: 1.33), most likely attributable to the sharp reduction in NOx emissions that lead to weaker NO titration effects (Zhao et al., 2020; Le et al., 2020). Zhao et al. (2020) statistically analyzed the air quality change one week before and one week after Level I response for Chinese cities. Their results show a similar correlation between Level I response and air quality. However, as we discussed earlier, our results measure the causal impacts of Level I response on air quality.

In Model (2), the coefficients of interaction term (β_2, β_3) of the treatment group and lockdown period are significantly negative for all indices except O_3, which indicates that the air quality of more severely affected cities by COVID-19 improved more than those cities with fewer cases. On average, the level of $PM_{2.5}$, PM_{10}, NO_2, SO_2 and CO for cities in D2 group (the cumulated confirmed cases between 10 and 99 as of March 28th, 2020) decreased by 8.18 μg/m^3 (Standard Error: 1.51), 15.38 μg/m^3 (Standard Error: 2.33), 6.05 μg/m^3 (Standard Error: 0.95), 0.64 μg/m^3 (Standard Error: 0.48) and 0.04 mg/m^3 (Standard Error: 0.02) more than those in D1 (accumulated cases less than 10 as of March 28th, 2020) when comparing lockdown with pre-lockdown period. In D3 group, which is the most affected group, the level of $PM_{2.5}$, PM_{10}, NO_2 and SO_2 decreased by 10.01 μg/m^3 (Standard Error: 1.76), 20.48 μg/m^3 (Standard Error: 2.34), 11.34 μg/m^3 (Standard Error: 1.05) and 0.64 μg/m^3 (Standard Error: 0.67) compared with D1 during the lockdown and pre-lockdown period, respectively. Similarly, the O_3 level increased more for those cities with more confirmed cases. As estimated by Model (2), the concentration level of O_{31} for Group 2 and Group 3 during the lockdown period shows insignificant difference when comparing to the least affected group (D1).

The DID results indicate that cities with more confirmed COVID-19 cases are associated with more changes in air quality is interesting, which are consistent with other studies for China (Wang et al., 2020) and India (Singh et al., 2020). Although all provinces and cities declare the highest response level, they implement the stay-at-home/lockdown orders differently as some essential productions and activities were still under way. It is expected that in most severely affected cities, these lockdown measures would be implemented extremely strictly. On the other hand, people voluntarily choose to stay at home due to the fear of infection, especially for people in those severely affected cities. As shown by Goolsbee and Syverson (2020), stay-at-home orders can only explain 11.6% of reduction in economic activities during this COVID-19 pandemic in the United States and economic activities are highly influenced by the number of COVID-19 deaths reported in the county. More data related to the traffic volume, production and economic activities, etc. could substantiate our understanding of the underlying mechanism of reductions in air pollution associated with lockdown.

The test results for possible heterogeneous regional effects of Level I

Table 1
Baseline regression results (Scenario 1: November 1, 2019 to response release).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variable	$PM_{2.5}$	PM_{10}	O_{31}	O_{38}	SO_2	NO_2	CO
Panel 1: Model (1) estimation							
T	−14.2681***	−22.1600***	15.5061***	17.0342***	−2.9403***	−17.6801***	−0.1751***
	(2.0897)	(2.3323)	(1.0368)	(1.3326)	(0. 3738)	(0.8314)	(0.0175)
Observations	34,963	34,944	34,963	34,963	34,963	34,963	34,963
R-Squared	0.373	0. 375	0. 449	0. 331	0. 569	0. 566	0. 454
Panel 1: Model (2) estimation							
T	−7.8047*** (2.3037)	−9.7345*** (2.8934)	16.2513*** (1.6474)	20.5804*** (2.3827)	−2.4588*** (0.5551)	−12.2507*** (0.9978)	−0.1615*** (0.0217)
D2_T	−8.1820*** (1.5127)	−15.3775*** (2.3346)	−1.6328 (1.7900)	−4.9093* (2.7210)	−0.6408 (0.4777)	−6.0462*** (0.9469)	−0.0351* (0.0196)
D3_T	−10.0066*** (1.7603)	−20.4832*** (2.3386)	1.2906 (2.1191)	−4.0010 (3.2933)	−0.6350 (0.6678)	−11.3362*** (1.0463)	0.0426 (0.0260)
Observations	34,963	34,944	34,963	34,963	34,963	34,963	34,963
R-Squared	0. 375	0. 380	0. 450	0. 332	0. 569	0. 575	0. 455

Note: the unit of CO is mg/m^3; the unit of other pollutants is μg/m^3. Standard errors are in parentheses, clustered at city level; $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Results of the coefficients of the key variable were reported due to space limits.

Table 2
Regional regression results (November 1, 2019 to response release).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variable	$PM_{2.5}$	PM_{10}	O_{31}	O_{38}	SO_2	NO_2	CO
Northern Cities							
T	−1.2245 (1.6202)	−8.2684*** (2.1399)	7.1261*** (0.6335)	9.7439*** (0.8707)	1.4515*** (0.3629)	−5.6348*** (0.5368)	−0.0454** (0.0180)
Observations	19,000	18,994	19,000	19,000	19,000	19,000	19,000
R-Squared	0.380	0.298	0.600	0.518	0.506	0.530	0.452
Southern Cities							
T	−7.7943*** (0.8374)	−10.6757*** (1.1644)	8.8864*** (1.2019)	11.8074*** (1.9123)	−0.6406** (0.2910)	−7.0457*** (0.7476)	−0.0126 (0.0120)
Observations	23251	23237	23251	23251	23251	23251	23251
R-Squared	0.351	0.339	0.370	0.256	0.489	0.574	0.474

Note: the unit of CO is mg/m^3; the unit of other pollutants is μg/m^3. Standard errors are in parentheses, clustered at city level; $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

response are presented in Table 2. The negative γ_1 for both northern and southern cities are consistent with our baseline model results. In southern cities, $PM_{2.5}$, PM_{10}, NO_2 and CO decreased by 7.79 μg/m^3 (Standard Error: 0.83), 10.68 μg/m^3 (Standard Error: 1.16), 7.05 μg/m^3 (Standard Error: 0.75) and 0.01 mg/m^3 (Standard Error: 0.01) due to the lockdown. In northern cities, $PM_{2.5}$, PM_{10}, NO_2 and CO decreased by 1.22 μg/m^3 (Standard Error: 1.62), 8.27 μg/m^3 (Standard Error: 2.14), 5.63 μg/m^3 (Standard Error: 0.54), and 0.05 mg/m^3 (Standard Error: 0.02) due to the Level I response policy. We also use another specification to test whether the differences between South and North are significantly greater than 0. It turns out that the differences of reduction in $PM_{2.5}$, PM_{10} and NO_2 are significant. The air quality improvements in southern cities are larger than that in northern cities in terms of the concentration of $PM_{2.5}$, PM_{10} and NO_2.

The smaller improvement of air quality due to lockdown in the North might be explained by two reasons. The first one is about the enforcement of Level I response policy. As most of the severely-affected cities are located in the South, there is a greater fear of the pandemic in the South which would reinforce the lockdown policy. Secondly, the Level I response policy restricts gathering and instructs people to stay at home where residential heating needs becomes higher.

One critical component of applying the DID model is the robustness check. The robustness of our benchmark results was tested using combination of different starting and ending dates of the sample (i.e. Scenario 2 and Scenario 3). The results of Scenario 2 (Table S4) and Scenario 3 (Table S5) are consistent with our benchmark results: the level of $PM_{2.5}$, PM_{10}, NO_2, SO_2 and CO concentrations decreased substantially during lockdown. These results suggest that our estimates are robust regardless of pollution indices and time periods.

3.4. Parallel trend test

To verify the dependent variables of cities in different groups have parallel trends before treatment, which is one of the basic assumptions of DID, we conduct a parallel trend test. After de-trending and centering the estimates on the day of Level I response announcement (*T*), Fig. 5 plots the estimate coefficients and the 95% confidence intervals, which are adjusted for city-level clustering.

As shown in Fig. 5, the coefficients on the lockdown dummy variables are insignificantly different from zero for days before Level I response announcement, with no trends in air quality prior to Level I response announcement. In addition, air quality falls immediately after lockdown, such that D_T^{+1} and D_T^{+2} is significantly below 0. To sum up, after controlling other impacting factors, air quality improvements do not precede lockdown, and air quality improves immediately after lockdown.

3.5. Avoided premature mortality during COVID-19

In this study, we attempt to estimate the premature mortality due to $PM_{2.5}$ exposure based on a concentration-response function. The results are shown in Fig. 6. During the lockdown period, the total premature mortality attributed to $PM_{2.5}$ exposure is estimated to be 263.3 thousand (95% CI: 190.5–305.1 thousand) for 278 cities. Stroke and IHD contribute to 97.0 thousand (95% CI: 69.4–111.6 thousand) and 80.2 thousand (95% CI: 57.4–92.3 thousand) premature death, together accounting for 67.3% of total $PM_{2.5}$-related premature death. COPD, LC, and ALRI contribute the rest 32.7% of premature death, each causing 44.2 thousand (95% CI: 33.9–53.9 thousand), 33.1 thousand (95% CI: 23.6–37.5 thousand), and 8.8 thousand (95% CI: 6.3–10.0 thousand). If no lockdown occurred, the average $PM_{2.5}$ is expected to increase by 14.3

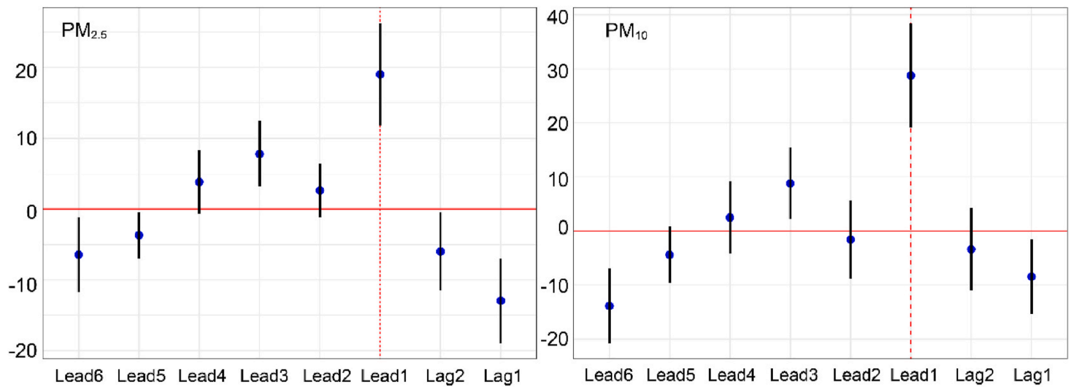

Fig. 5. Impact of lockdown on $PM_{2.5}$ and PM_{10}.

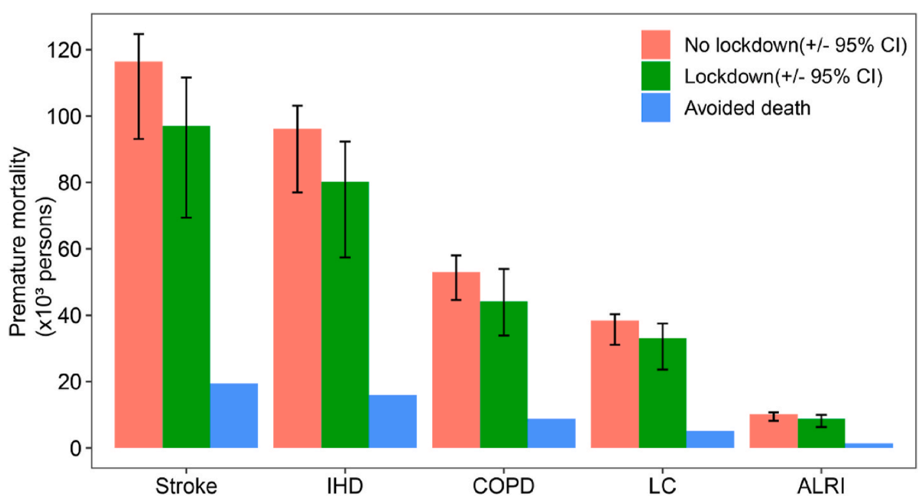

Fig. 6. Premature death due to $PM_{2.5}$ exposure and avoided death due to $PM_{2.5}$ reductions during lockdown.

μg/m^3 on average based on the DID results. The total $PM_{2.5}$-related premature mortality is then estimated to be 314.2 thousand (95% CI: 254.0–336.8 thousand), representing a decrease by 16.1%. The relative contributions from different diseases stay unchanged. Comparing the premature mortality of the actual and simulated scenario, the avoided premature death due to lockdown is estimated to be 50.8 thousand, representing 19.3% of the estimated premature mortality during Level I response. Reduction in cardiovascular disease (stroke and IHD) mainly contributes to the avoided premature mortality, which are 19.4 thousand (38.1%) and 16.0 thousand (31.5%), respectively.

These numbers represent a preliminary estimate of the health impacts associated with COVID-19 lockdown. The use of population-weighted $PM_{2.5}$ concentration for all cities instead of using city-level $PM_{2.5}$ concentration results in a relatively conservative estimate. As mentioned in our previous study (Huang et al., 2020), uncertainties exist with this preliminary estimate, including but not limited to the uncertainties of the concentration-response coefficient, the heterogeneities of $PM_{2.5}$ concentrations within the cities is ignore, the health impacts associated with ozone exposure was not considered in the study, which could partially offset the health benefits brought by $PM_{2.5}$ reductions.

4. Conclusions

The outbreak of COVID-19 has led to substantial reductions in anthropogenic emissions due to restricted production, economic and social activities. In this study, the application of the difference-in-differences method allows us to investigate the causal impact of COVID-19 on changes in air quality at 278 cities across China. Our DID results show that lockdown has caused substantial reductions in concentrations of all criteria pollutants except ozone. If no lockdown occurred, the averaged concentration of $PM_{2.5}$ would increase by 14.3 μg/m^3. The total avoided premature death associated with reductions in $PM_{2.5}$ concentration is estimated to be 50.8 thousand, representing 19.3% of total premature death during Level I response. However, by no means this study should be interpreted that pandemics have a positive effect on health.

Results from the DID model confirms that the air quality of cities with more cases of COVID-19 exhibits stronger response to lockdown. In addition, Level I response has a heterogeneous effect on air quality improvement for southern and northern cities. The parallel trend tests find that the air quality for cities in different groups had similar trends before the Level I response. The air quality improvements do not precede lockdown, and air quality improves immediately after lockdown. All these results confirm a causal relationship between lockdown and air quality improvements, especially for those cities with more confirmed cases and southern cities. The robustness check results show the main conclusion does not change by using different sample periods for controls. A more robust DID model should incorporate the post lockdown period and test whether the air quality has gotten worse after Level I response. A more specific model that explicitly models production and transportation decisions is necessary to explore the mechanisms for COVID-19 impacts on air quality.

Our results have important policy implications. First, the results re-emphasize the importance of emission reductions in mitigating the adverse health impacts associated with air pollution and continuous efforts are needed to reduce concentrations of $PM_{2.5}$ and ozone simultaneously. Second, the pollution mitigation policy would be more effective if the policies are incentive compatible, i.e., people/firm would abide by the policies if the policies are in their interest. Third, the extremely high cost of lockdown, still high level of air pollution during lockdown and smaller effects in northern cities implies that we need source-specific mitigation policies.

Credit author statement

Y. M. Li, S. L. Li, and L. Huang designed the research. L. Huang and S. Y. Li collected data. Y. M. Li and S. Y. Li performed modeling work. L. Huang, Z.Y. Liu, and Y.H. Zhu helped with the methods. Y. M. Li, L. Huang and S.Y. Li wrote the paper with contributions from all co-authors.

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envpol.2021.117988.

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