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Effects of COVID-19 lockdown on global air quality and health

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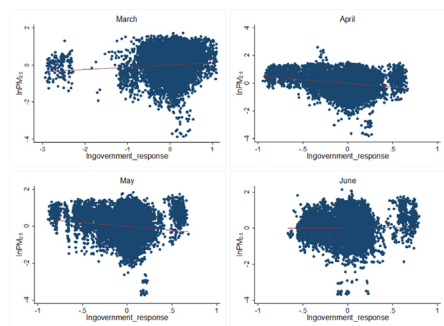
HIGHLIGHTS

- The relationship between 8 different lockdown measures and air pollution worldwide was quantitively examined.
- A novel COVID-19 government response tracker dataset was used in the empirical analysis.
- NO_2 falls more precipitously, followed by PM_{10}, SO_2, $PM_{2.5}$, and CO, but O_3 increases relative to pre-lockdown period.
- The expected premature deaths due to improved air quality decline by around 99,270 to 146,649 among 76 countries and regions.

GRAPHICAL ABSTRACT



The daily government response index and $PM_{2.5}$ concentrations of 597 cities worldwide from March to June 2020.

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ABSTRACT

The COVID-19 pandemic has put much of the world into lockdown, as one unintended upside to this response, the air quality has been widely reported to have improved worldwide. Existing studies examine the environmental effect of lockdowns at a city- or country-level, few examines it from a global perspective. Using a novel COVID-19 government response tracker dataset, combining the daily air pollution data and weather data across 597 major cities worldwide between January 1, 2020, and July 5, 2020, this study quantifies the causal impacts of 8 types of lockdown measures on changes of a range of individual pollutants based on a difference-in-differences design. The results show that the NO_2 air quality index value falls more precipitously (23–37%) relative to the pre-lockdown period, followed by PM_{10} (14–20%), SO_2 (2–20%), $PM_{2.5}$ (7–16%), and CO (7–11%), but the O_3 increases 10–27%. Furthermore, intra/intercity travel restrictions have a better performance in curbing air pollution. These results are robust to a set of alternative specifications, including different panel sizes, independent variables, estimation strategies. The heterogeneity analysis in terms of different types of cities shows that the lockdown effects are more remarkable in cities from lower-income, more industrialized, and populous countries. We also do a back-of-the-envelope calculation of the subsequent health benefits following such improvement, and the expected averted premature deaths due to air pollution declines are around 99,270 to 146,649 among 76 countries and regions involved in this study during the COVID-19 lockdown. These findings underscore the importance of continuous air pollution control strategies to protect human health and reduce the associated social welfare loss both during and after the COVID-19 pandemic.

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1. Introduction

Starting in December 2019, the first cases of pneumonia caused by a novel coronavirus were reported in Wuhan, the capital city of Hubei Province in central China. Thereafter, the number of detected and confirmed cases increased rapidly as the virus is capable of spreading through human-to-human contact (Chan et al., 2020). World Health Organization (WHO) officially named this novel virus as coronavirus disease 2019 (COVID-19) on February 11, 2020, when more than 3000 cases confirmed globally and about 97 people known to have died, and almost all of them were found in China only (WHO, 2020). While COVID-19 does not stop there, its high transmissibility and high infectivity help it spread globally, the human cost of it continues to mount. As of September 7, 2020, a total of 27,032,617 cases detected and confirmed and claimed 881,464 dies across more than 200 countries since the outbreak of it (WHO, 2020). When the authors are writing this paper, most of the world remains in the shadow of COVID-19, many countries are still seeing accelerating death tolls. Given the devastating health impacts of COVID-19, many countries implemented a wide range of strict non-pharmaceutical interventions (NPIs) to slow the infection rate. The primary one of NPIs is human mobility restrictions or social distancing regulations, that is lockdown, which have dramatically transformed people's daily lives worldwide. As the epicenter of the pandemic, China was the first country to impose city lockdown policy on January 23, 2020, when the imposed lockdown of Wuhan was put into implementation, and in other Hubei cities several days later. After March 2020, more than 140 countries had enforced lockdown policies according to the Oxford COVID-19 Government Response Tracker (OxCGRT).[4] These lockdown policies have created the most extensive quarantine in public health history, which leads to various socio-economic consequences on our day-to-day activities. Interestingly, among these consequences, a perceived air pollution reduction was confirmed in many countries (Watts and Kommenda, 2020; Sharma et al., 2020; Li et al., 2020), even in a global level (Venter et al., 2020). As lockdowns constrain social interactions and thus socio-economic activities that rely on such interactions, particularly a dramatic decrease in industrial activity and vehicle use in cities, which results in a drastic reduction in air pollutant emissions (Cole et al., 2020). Since the outbreak of COVID-19, some researchers have examined the environmental effect associated with it due to the implementation of a wide range of NPIs (e.g., school and workplace closures, partial or strict lockdown). While most focused on a specific city or country, few examined the environmental effects of lockdown from a global perspective, thus this study plans to fill this gap.

This paper uses the worldwide daily air pollution data and weather data and a COVID-19 government response tracker dataset to investigate changes in air quality at the global level to widespread pandemic response strategies. Our strategy for examining the causal effect of lockdowns on air quality relies on a comparison of changes in air pollutant species, including particulate matter (PM_{10} and $PM_{2.5}$), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), carbon monoxide (CO), and ozone (O_3) within a city around the lockdown dates. In order to eliminate the confounding factors, researchers have to adopt quasi-experimental strategies to investigate the causal effects of COVID-19 responses. Two sets of difference-in-differences (DID) analyses are adopted in this study, which provide important advantages over other empirical strategies such as before-and-after comparisons and interrupted time-series designs through introducing control groups (Tobías, 2020). Moreover, an unbiased DID evidence could provide timely and accurate causal estimates for COVID-19 policymaking to avoid serious consequences (Goodman-Bacon and Marcus, 2020). Our study may contribute to the policy intervention–air quality literature in the following four areas. First, our empirical specification used comprehensive data at a day-by-city level from January 1 to July 5, 2020, covering the daily median of individual air quality index (AQI) of PM_{10}, $PM_{2.5}$, NO_2, SO_2, CO, and O_3 across 597 major cities in the world and corresponding lockdown information, which contributes to quantifying the impacts of pandemic-induced lockdowns on cities' air quality from a global perspective. Second, the overall government response index from OxCGRT dataset was added into our DID design to construct a two-way fixed effects (TWFE) event-study specification according to Correia et al.'s (2020) and Callaway and Sant'Anna's (2018) researches to handle DID with multiple time periods. Besides, this dataset also provides 8 different lockdown measures that allowing us to compare the impacts on air quality from different lockdown measures. Therefore, we would learn lessons from this comparison that provides references and insights in formulating environmental regulations during the recovery period. Third, this study examined the evidence for heterogeneous environmental impacts from lockdowns among countries differed in development level, industrial structure, and population. It allowed us to make a cross-country comparison and informed governments that taking measures suitable to local conditions should be the basic principle when charting paths to counter air pollution during the post-pandemic period. Last, we also provided some back-of-the-envelope calculations on the expected health benefits from the apparent air quality improvement, which contributed to the literature on the health costs of changes in air pollution concentrations associated with specific causes.

The rest of this paper is outlined as follows. Section two presents a summary of the datasets used in this study, while the third section presents different empirical strategies. Section 4 presents the results, which form the basis for the discussion on the heterogeneity and health implications of our findings. In Section 5, we conclude.

2. Data and descriptive statistics

2.1. Air pollution and weather data

We collected the daily air pollution data for a range of pollutants of cities across the world between January 1, 2020, to July 5, 2020 from the Air Quality Open Data Platform, a new dedicated dataset that provides worldwide air quality data.[5] The air pollution data for each major city is based on the average (median) of its monitoring stations, covering air pollutant species ($PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, and O_3). Daily weather variables, including humidity, temperature, and wind speed are also controlled in our specification given the determinant role of local weather conditions in affecting the air quality (Gendron-Carrier et al., 2018), which are also collected from the Air Quality Open Data Platform. Given the data availability and coverage, we use the median value of the air pollution level and weather variables in each city.

Fig. 1 shows the daily changes in $PM_{2.5}$ individual AQI (converted from corresponding concentrations based on the US EPA standard) of study area cities during the sample period and at the same time frame in 2019, which suggests that cities experienced a similar air pollution level before the date of Wuhan lockdown (the first city in the world to impose city lockdown policy) when the COVID-19 had not spread worldwide, and few cities were put under strict lockdown compared with the same period last year. However, the difference significantly increased, especially after March 2020, when more cities were locked down, indicating an air quality improvement occurred after city lockdowns.

[4] More information about this dataset will be presented in Section 2.

[5] More information about the dataset can be found at https://aqicn.org/data-platform/covid19/verify/9fbd8433-2ab9-403d-9392-43851e866615.

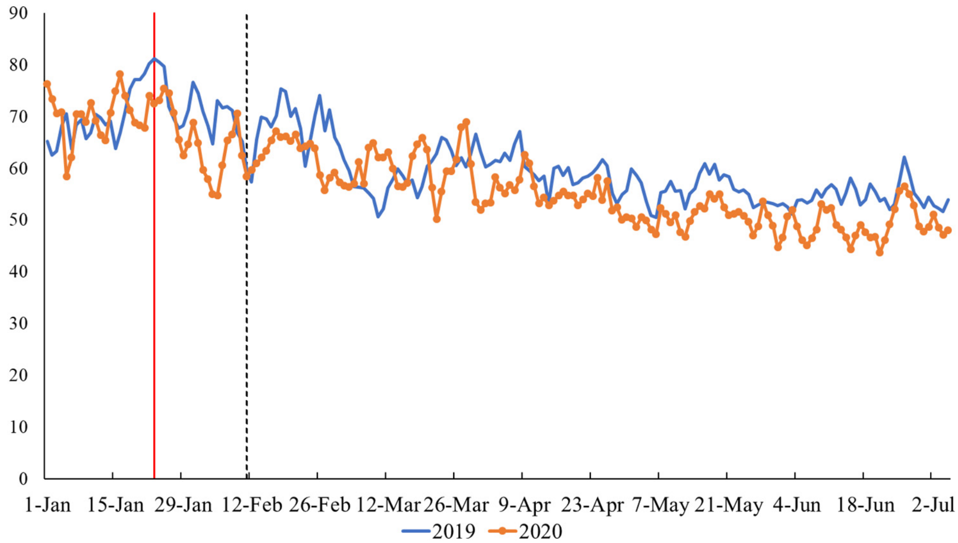

Fig. 1. The global trend of air pollution: $PM_{2.5}$. *Notes*: The solid red line indicates the date of Wuhan lockdown (January 23, 2020), and the black dash line indicates the date that this novel coronavirus received an official name from WHO (February 11, 2020). Data comes from the aqicn.org (https://aqicn.org/data-platform/covid19/).

2.2. Lockdown measures data

We obtained lockdown measures data from Oxford University's Blavatnik School of Government, OxCGRT database (Hale et al., 2020). This source provides a range of government lockdown measures to the pandemic, including school and workplace closures, movement (internal or international) and gatherings restrictions, and stay-at-home requirements across the world, updated daily. We collected the lockdown measures-related information for each country up to and including July 5, 2020.

With the outbreak of COVID-19, different governments employed a wide range of lockdown measures to contain the virus, which posed a challenge to researchers who want to make a comparative analysis over time or between countries. In this connection, a team at Oxford University's Blavatnik School of Government established a database of pandemic-response policies, based on which an index of the measures' overall stringency was calculated. This dataset tracks individual policy measures across 17 indicators (13 ordinal indicators and 4 non-ordinal indicators) that are organized into three groups (i.e., containment and closure policies, economic policies, and health system policies), as for those do not fit elsewhere are recorded by a miscellaneous indicator. Given the focus of this study is on the lockdown-induced air quality change, we collected containment and closure policies to denote governments' lockdown measures. Table 1 reports the specific descriptive statistics of various lockdown measures used in this study.

Based on these individual component indicators, this team also calculates four indices, each of them reports a number between 0 and 100, to reflect the overall impression of governments' pandemic responses.[6] Specifically, the government response index, the containment and health index, the stringency index, and the economic support index, all of which are calculated based on individual ordinal indicators where policies are ranked on a simple numerical scale. As the government response index covers all 13 ordinal indicators that take containment and closure policies, economic support policies, and health system policies into consideration, which allow us to have a comprehensive understanding of the imposed lockdown measures.[7] Therefore, this study introduces it into our empirical specification to conduct the event-study based DID analysis.

Fig. 2 presents a plot of the government response index worldwide on March 1, 2020, and July 1, 2020. It can be seen that the stringency in most countries has generally increased over time. This increase has been mainly driven by the worsening pandemic across the world, which is likely to induce a change in air pollutants.

2.3. Data matching and descriptive statistics

We matched the abovementioned two datasets into a city-day level panel between January 1, 2020, and July 5, 2020, for subsequent empirical analysis. All the cities with air pollution data and corresponding meteorological variables were matched with the lockdown dates of their belonging countries. Since the Oxford team does not collect any sub-national data on lockdown measures, the potential problem may be that there exists the time inconsistency in lockdown dates among different cities in a specific large or federal country. However, as we only focus on major cities around the world that are generally the first group to be put under strict lockdown in each country, thus their lockdown dates are consistent with those from OxCGRT at the national level. Finally, our study includes 597 cities from 76 countries and regions (as shown in Fig. 3), covering 81% of the global population.[8]

Fig. 4 plots a city-level scatterplot of $PM_{2.5}$ individual AQI against the government response index, between March and June 2020. The negative trend was particularly striking in April and May as most cities were put under a strict lockdown after March 2020. While many governments have started to plot paths to easing the lockdown measures as the new confirmed infections and COVID-related deaths

[6] More information about the calculation of different indices can be found at https://github.com/OxCGRT/covid-policy-tracker/blob/master/documentation/index_methodology.md.

[7] Two metrics of economic support policies, including income support and debt/contract relief, and two extra metrics of health system policies, including testing policy and contact tracing are used when calculating the government response index. The former two metrics help relieve households' pressure from income reduction hence their economic activities would, to a lesser degree, reduce. Consequently, the air pollution reduction effect caused by lockdown may be offset by these policies. In contrast, the latter two metrics of health system policies further restrict the travel of individuals then strengthening the lockdown effect. Therefore, the government response index is capable of giving a holistic picture of lockdown measures.

[8] The full list of 597 cities and corresponding monitoring stations are available in Appendix A.

Table 1
A summary of lockdown measures.

Name	Measurement	N	Mean	S. D.	Min	Max
School closing (C1)	0 - no measures; 1 - recommend closing; 2 - require closing; 3 - require closing all levels.	105,251	1.770	1.390	0	3
Workplace closing (C2)	0 - no measures; 1 - recommend closing; 2 - require closing for some sectors or categories of workers; 3 - require closing for all-but-essential workplaces.	105,375	1.340	1.224	0	3
Cancel public events (C3)	0 - no measures; 1 - recommend cancelling; 2 - require cancelling.	105,296	1.215	0.928	0	2
Restrictions on gatherings (C4)	0 - no restrictions; 1 - restrictions on very large gatherings (the limit is above 1000 people); 2 - restrictions on gatherings between 101 and 1000 people; 3 - restrictions on gatherings between 11 and 100 people; 4 - restrictions on gatherings of 10 people or less.	105,375	1.868	1.835	0	4
Close public transport (C5)	0 - no measures; 1 - recommend closing (or significantly reduce; volume/route/means of transport available); 2 - require closing (or prohibit most citizens from using it).	105,398	0.533	0.730	0	2
Stay at home requirements (C6)	0 - no measures; 1 - recommend not leaving house; 2 - require not leaving house with exceptions for daily; exercise, grocery shopping, and 'essential' trips; 3 - require not leaving house with minimal exceptions.	105,409	0.970	1.044	0	3
Restrictions on internal movement (C7)	0 - no measures; 1 - recommend not to travel between regions/cities; 2 - internal movement restrictions in place.	105,357	0.974	0.926	0	2
International travel controls (C8)	0 - no restrictions; 1 - screening arrivals; 2 - quarantine arrivals from some or all regions; 3 - ban arrivals from some regions; 4 - ban on all regions or total border closure.	105,367	2.217	1.556	0	4

Notes: All data come from the OxCGRT database that range from January 1, 2020, to July 5, 2020.

showed a slowing or declining trend. Besides, the economic crisis caused by crippling lockdowns increased the pressure of governments to reopen schools and businesses since June; thus, the negative trend became less significant after June. The figure shows the dynamics of the intensity of lockdown measures and corresponding air pollution levels, suggesting that there may exist a negative association between them, which need additional causal empirical evidence.

Table 2 reports the descriptive statistics of other key variables involved in this study besides the lockdown measures. The average government response index during COVID-19 was around 46, and the average stringency index was about 47, which suggested a relatively high level of restriction on anthropogenic activities persisted during the sample period.

3. Empirical strategy

In this section, we introduce the empirical approaches used in this study. We started by quantifying the impact of lockdown measures on air quality through a fixed-effects Ordinary Least Squares (OLS) approach. Then we employed a "traditional" DID method to examine the lockdown effect on air quality due to the outbreak of pandemic to achieve a baseline result. Moreover, we also constructed a government response index-based DID model as well as a set of alternative strategies to confirm the robustness of our baseline result.

3.1. Fixed-effects ordinary least squares

As for the time series model, the most straightforward strategy is to simply estimate it by OLS. For each pollutant $p \in \{PM_{2.5}, PM_{10}, CO, NO_2, SO_2, O_3\}$ in city i of country m at time t:

$$\begin{aligned} Air\ quality^{p}_{mit} &= \theta_1 City_i + \theta_2 Country_m + \theta_3 \mathrm{Date}_t + \theta_4 Lockdown^{n}_{mit} \\ &+ \boldsymbol{\theta_5} Weather_{mit} + \theta_6 Trend_{it} + \theta_7 Trend^{1}_{mt} + \delta_{mit} \end{aligned} \tag{1}$$

where, $Air\ quality^{p}_{mit}$ denotes the air quality represented by air pollutant p of city i in country m at time t. The key explanatory variable is the lockdown measures, $Lockdown^{n}_{mit}$, $n = 1, \ldots, 8$ is the index for eight types of lockdown measures. $Weather_{mit}$ is a vector of weather variables including humidity, temperature, and wind speed. We include city and country fixed effects ($City_i$ and $Country_m$) to control for unobserved city and country attributes that affect air quality. The date-fixed effect ($Date_t$) is also controlled to eliminate the time-specific impact. To avoid other confounding factors that may be inconsistent across time while are not adequately controlled by $Date_t$, we include a city-by-day variable that captures time-varying city-specific trends. Similarly, we also interact the dummy for country m and the linear time trend t ($Trend^{1}_{mt}$) to alleviate the endogeneity concerns in terms of the time-varying country-specific unobservables. δ_{mit} denotes the random error term. The authors expect θ_4 to capture a negative relationship between the stringency of lockdown measures and air quality. As stricter lockdown measures restrict more internal or international interactions and associated socio-economic activities that rely on such interactions, which lead to a dramatic decline in emissions.

3.2. The difference in differences specification

Considering the potential endogeneity and omitted variable bias of the simple time-series regression and year-over-year comparisons, we use two sets of DID models to more accurately account for the expected drop in air pollution following the implementation of lockdown measures. First, in our baseline estimate, we identify the relative change in the impact of lockdown measures on air pollution levels between cities from the treated and control group. The specification is:

$$\begin{aligned} Air\ quality^{p}_{mit} &= \theta_1 T\_Lockdown^{n}_{mit} + \theta_2 City_i + \theta_3 Country_m + \theta_4 Date_t \\ &+ \boldsymbol{\theta_5} Weather_{mit} + \theta_6 Trend_{it} + \theta_7 Trend^{1}_{mt} + \delta_{mit} \end{aligned} \tag{2}$$

where the coefficient of interest, θ_1, is the effect of imposed lockdown measures on air quality. The variable $T\_Lockdown^{n}_{mit}$ is one of the eight lockdown measures indicators after transformation that takes a value of zero for days without lockdown measures in city i of country m at time t, and a value of one for all days after the lockdown measures are enforced. As shown in Table 1, the lockdown measures-related information is recorded by ordinal indicators, for instance, the school closing policy that records closings of schools and universities is ranked by 0, 1, 2, and 3; the stringency of this policy increases with the increase of its ordinal value. As a DID design compares changes in air quality before and after lockdown measures takes effect in one city, to changes in the air quality in another city that did not impose lockdown measures. For comparison's sake, we transformed the school closing policy indicator into a binary variable. Specifically, we did not distinguish between school closing policies that differed in stringency and assigned them to the value of 1, while assigning the value of 0 to days that no associated lockdown measures are enforced. The other seven lockdown measures were handled with the same method.

In addition to the "traditional" DID, we also estimate a government response index-based DID specification based on the research of Correia et al. (2020), the specific specification is:

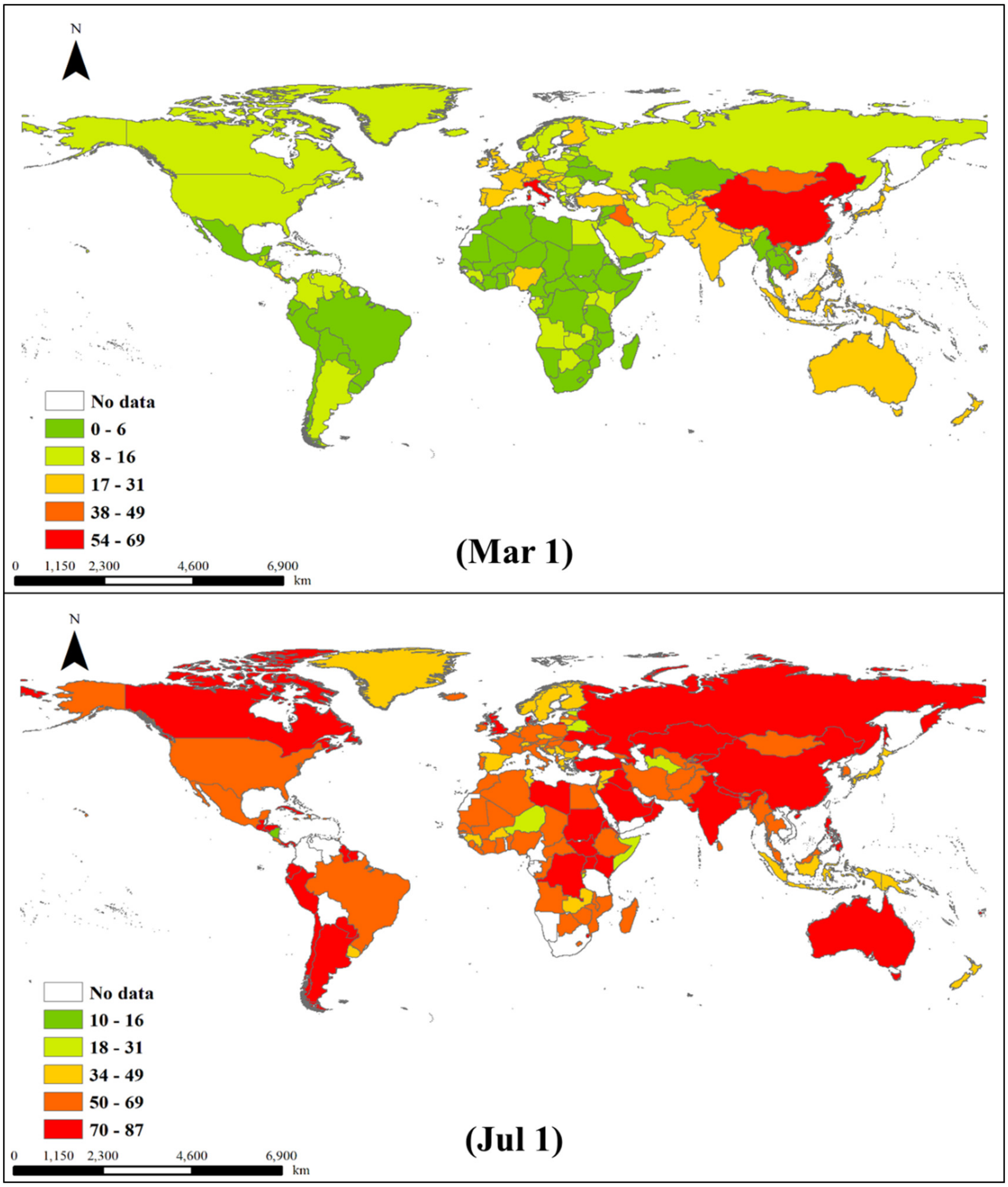

Fig. 2. Changes in the government response index across the world.

$$Air\ quality^{p}_{mit} = \theta_1 GRI_{mit} \times T\_Lockdown^{n}_{mit} + \theta_2 City_i + \theta_3 Country_m + \theta_4 Date_t + \boldsymbol{\theta_5} Weather_{mit} + \theta_6 Trend_{it} + \theta_7 Trend^{1}_{mt} + \delta_{mit} \quad (3)$$

where GRI_{mit} denotes the government response index from the OxCGRT database; the rest of control variables are the same as Eq. (2). The coefficient θ_1 estimates the difference in air pollution level between the treated cities and the control cities before and after the enforcement of the lockdown measures. Different from the “traditional” DID, we add the government response index in this DID analysis, which allows us to compare the difference in the effects of a marginal change in the government response index on equilibrium air quality between treated units and the untreated units. We expect the coefficient θ_1 to be negative, as most major cities experience an increase in the value of government response index during the sample period, which would significantly restrict their industrial and business activities hence less emissions of various air pollutants.

Since the key assumption of DID analysis is that treated and control cities follow parallel trends in the absence of lockdown measures. To test this assumption, we also recast the data in an “event study” analysis following Correia et al. (2020), the DID framework is specified as:

$$Air\ quality^{p}_{mit} = \sum\nolimits_{d \neq -1} \beta_d GRI_{mit} \mathbf{1}_{d=t} + \theta_2 City_i + \theta_3 Country_m + \theta_4 Date_t + \boldsymbol{\theta_5} Weather_{mit} + \theta_6 Trend_{it} + \theta_7 Trend^{1}_{mt} + \delta_{mit} \quad (4)$$

where $-185 \le d \le 186$ indicates leads and lags of the launch of the lockdown measures. The dummy for $d = -1$, as the base interval, is omitted

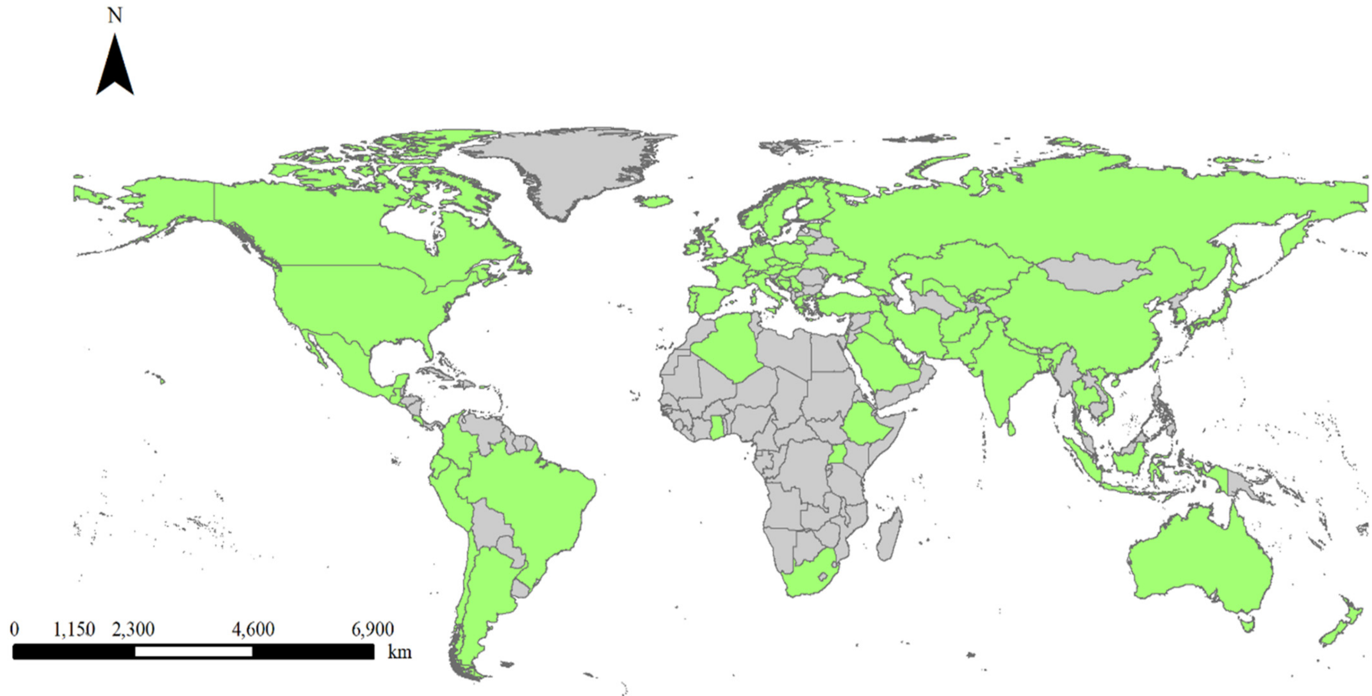

Fig. 3. The geographic distributions of countries and regions involved in this study. *Notes*: Gray areas denote non-study areas.

in our regression. $\mathbf{1}_{d=t}$ are a set of binary variables indicating the treatment status at different periods. The event-study coefficient, β_d with $d \geq 0$ can be interpreted as average treatment effect parameters at day d, while β_d with $d \leq -2$ can be used to assess the credibility of the parallel trend assumption. Panels (a)–(h) of Fig. 5 plots the β_d coefficients together with their pointwise 95% confidence intervals, which capture the relative dynamics in the air quality of cities with a higher level of government response.

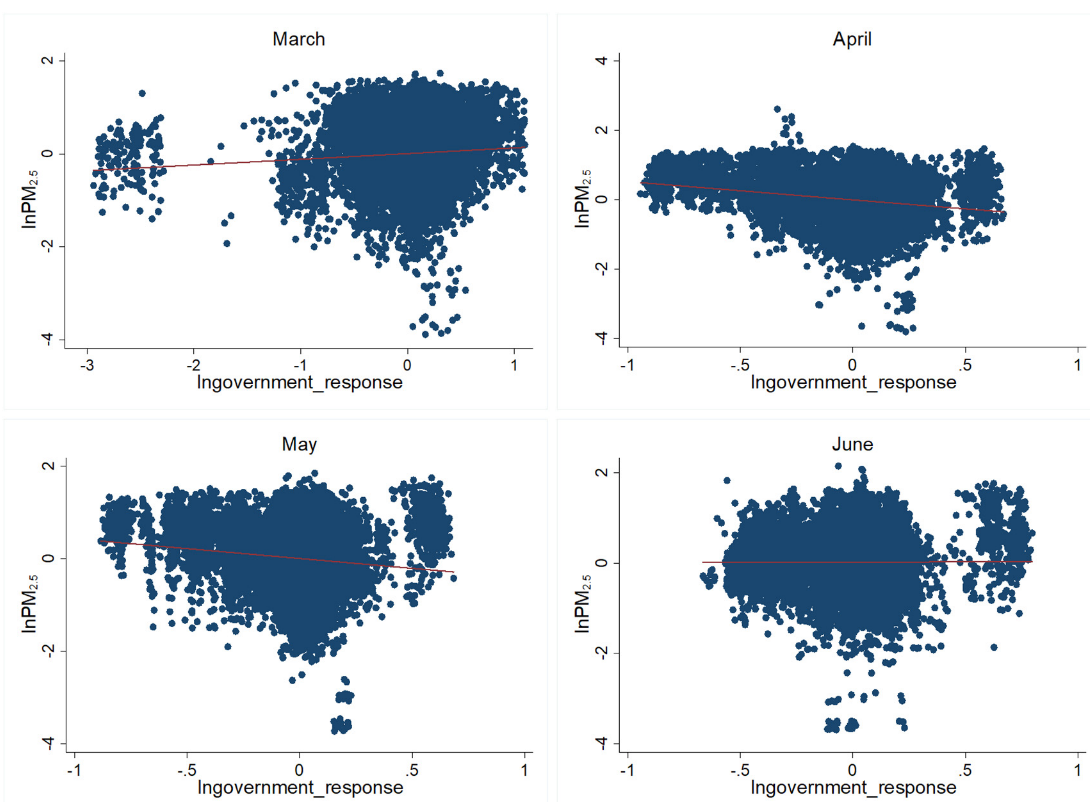

Fig. 4. The daily government response index and $PM_{2.5}$ individual AQI of 597 cities worldwide involved in this study from March to June 2020. *Notes*: Both indicators are logarithmically transformed in order to avoid the nonnormality and heteroscedasticity. The red line indicates the trend line, which predicts the overall relationship between $PM_{2.5}$ individual AQI and the intensity of the government response index.

Table 2
Descriptive statistics during COVID-19 (2020/1/1–2020/7/5).

Variables	N	Mean	S. D.	Min	Max
$PM_{2.5}$	91,518	53.45	40.17	1	834
PM_{10}	90,391	26.22	23.09	1	882
SO_2	75,040	4.040	7.810	0	500
NO_2	89,935	9.040	7.140	0	166.6
O_3	83,917	21.68	10.94	0	274
CO	69,265	5.480	11.73	0.100	500
Humidity	99,155	66.88	19.41	0	122
Temperature	99,184	15.08	9.100	−50	93.30
Wind speed	95,034	3.031	6.121	0.1	259.4
Government response index	105,117	45.58	30.22	0	96.15
Containment and health index	105,176	47.73	31.14	0	100
Stringency index	105,233	46.52	33.02	0	100
Economic support index	105,226	33.85	35.85	0	100

Notes: The wind speed data are not available in February and March 2020 in the Air Quality Open Data Platform; hence we collect the corresponding data of these two months from NOAA instead. All air pollutant species have been converted to the US EPA standard, the value here corresponds to the individual pollutant AQI and the scale convertor can be found at: http://aqicn.org/calculator/cn/.

The estimates show that, relative to the period immediately before the launch of lockdown measures, cities with a higher level of government response had a lower level of air pollution from the day that lockdown measures are enforced onward than those with more lenient government responses. Therefore, the results support the parallel trends assumption in general, we also estimate the event-study regression specification of other five air pollutants based on Eq. (4), also found no systematic difference in the trends between treated and control cities in the absence of city lockdown measures. The results are not presented here due to the limit of space, which is available upon request.

4. Empirical results

In this section, we first presented the estimated impacts of lockdown measures on air quality using the fixed-effects OLS and the DID method in the first two subsections, followed by a set of alternative strategies for the robustness test. After that, the heterogeneous effects of lockdown for different cities and the health implication out of the air quality improvement were also presented.

4.1. Estimates based on fixed-effects OLS

Table 3 presents the results from fixed-effects OLS estimates on $PM_{2.5}$ based on Eq. (1) above. Each column reports the results with different lockdown measures as the key independent variable. The results indicate that the stringency of lockdown measures is positively related to the air pollution level denoted by the $PM_{2.5}$ individual AQI, and this result is statistically significant at the 1% level for each type of lockdown measure. The estimations of weather variables are consistent with our intuitive judgments except for the temperature. Both high wind speed and humidity contribute to the dispersion of air pollutants hence improving the air quality. The negative relationship between temperature and air pollution level could reflect a possibility that most cities in our sample are located in the mid-latitudes of the northern hemisphere, whose winter starts December 1 and lasts 3 months (December, January, and February) with spring season (March, April, and May) and summer season (June, July, and August). As our sample period is from January 1 to July 5, 2020, most major cities in our sample generally experienced a gradual rise in temperature. However, these cities to come under lockdown since the coronavirus outbreak worldwide in March. Then production in many factories had been halted, and human travel had been restricted to prevent the spread of the virus; consequently, a dramatic drop-off in air pollution worldwide is recorded. Furthermore, the winter season usually witnesses periods of worse air pollution within a year owing to the extra heating needs. So, a negative association exists between the air pollution level and temperature during the sample period.

We also present the estimates of the other five air pollutants based on Eq. (1), the results are reported in Table 4. Eight columns are presented, the different columns alter the key independent variable. Each pollutant estimates are consistent with Table 3 except O_3. Panel F shows that the enforcement of various lockdown measures is positively associated with O_3 individual AQI, which is consistent with Venter et al.'s (2020) findings based on the satellite data from a global perspective. This positive association is probably related to the source of O_3, as it is not primary but forms in the atmosphere from chemical reactions (Deschênes et al., 2017). The activity-emission-concentration relationship for O_3 is more sensitive to a set of atmospheric processes rather than emissions from transport or other sources. Interestingly, we can find that cities experience a reduction in air pollution when imposing closing public transport policy. This finding is consistent with Beaudoin and Lin Lawell's (2016) and Rivers et al.'s (2020) conclusions that public transit contributes to the increase of local pollution levels. Since existing public transport systems worldwide are still dominated by buses that typically burn diesel, restricting the provision of public transit would result in a reduction in vehicle emissions. Therefore, governments should promote the development of rail transit and other low-emission public transport and taking the environmental consequences into account in public transport planning. The relative smaller magnitude of lockdown effects on air pollution from the stay at home requirements may be attributable to the limited adoption of it worldwide (18 out of 76 countries stringently enforced this restriction at peak). In general, these findings suggest the effectiveness of restrictions on intra/intercity travel in curbing air pollution, which inform governments of formulating more policies on air pollution abatement from the perspective of transportation during the "normal" times.

4.2. Difference-in-difference estimates

We report the baseline results of this study in Table 5 based on the DID specification. The coefficient θ_1 in Eq. (2) reflects the relative change in air quality in cities with lockdown to those without enforcing lockdown measures. The results show that locked-down cities experience a larger reduction in air pollution levels, specifically, the daily $PM_{2.5}$, PM_{10}, SO_2, NO_2, and CO individual AQI declined by 3.7–9.6, 3.3–5.5, 0.1–0.9, 2.7–4.2, and 0.4–0.7 unit, respectively; this translates respectively to 7–16%, 14–20%, 2–20%, 23–37%, and 7–11% decrease at the threshold. We can find that the NO_2 individual AQI experiences a steeper decline than the other five air pollutants. This finding suggests that lockdown measures have largely restricted human travel by cars or buses, which are the major sources of ambient nitrogen dioxide. The insignificant decline in SO_2 individual AQI under restrictions on international travel, which is primarily related to industrial activities, indicating the impact of this type of lockdown measure on industrial activities is likely to be marginal. Moreover, the positive relationship between the individual AQI of O_3 and lockdown measures still holds. In general, lockdown measures improved air quality substantially across the world except for the reduction in the individual AQI of O_3. The baseline results are consistent with the estimates with fixed-effects OLS model. The DID estimates, however, are considerably larger in magnitude than fixed-effects OLS estimates, indicating fixed-effects OLS estimates are biased downward, possibly due to omitted variable bias and/or measurement error.

We also presented a government response index-based DID estimates as an alternative specification, the estimating results are presented in Table 6. It can be found that the negative relationship between lockdown measures and air pollution levels persists, but the magnitude of a change in the AQI value of air pollutants caused by lockdown measures is smaller than the estimates presented in Table 5. In general, across all eight lockdown measures, a higher government

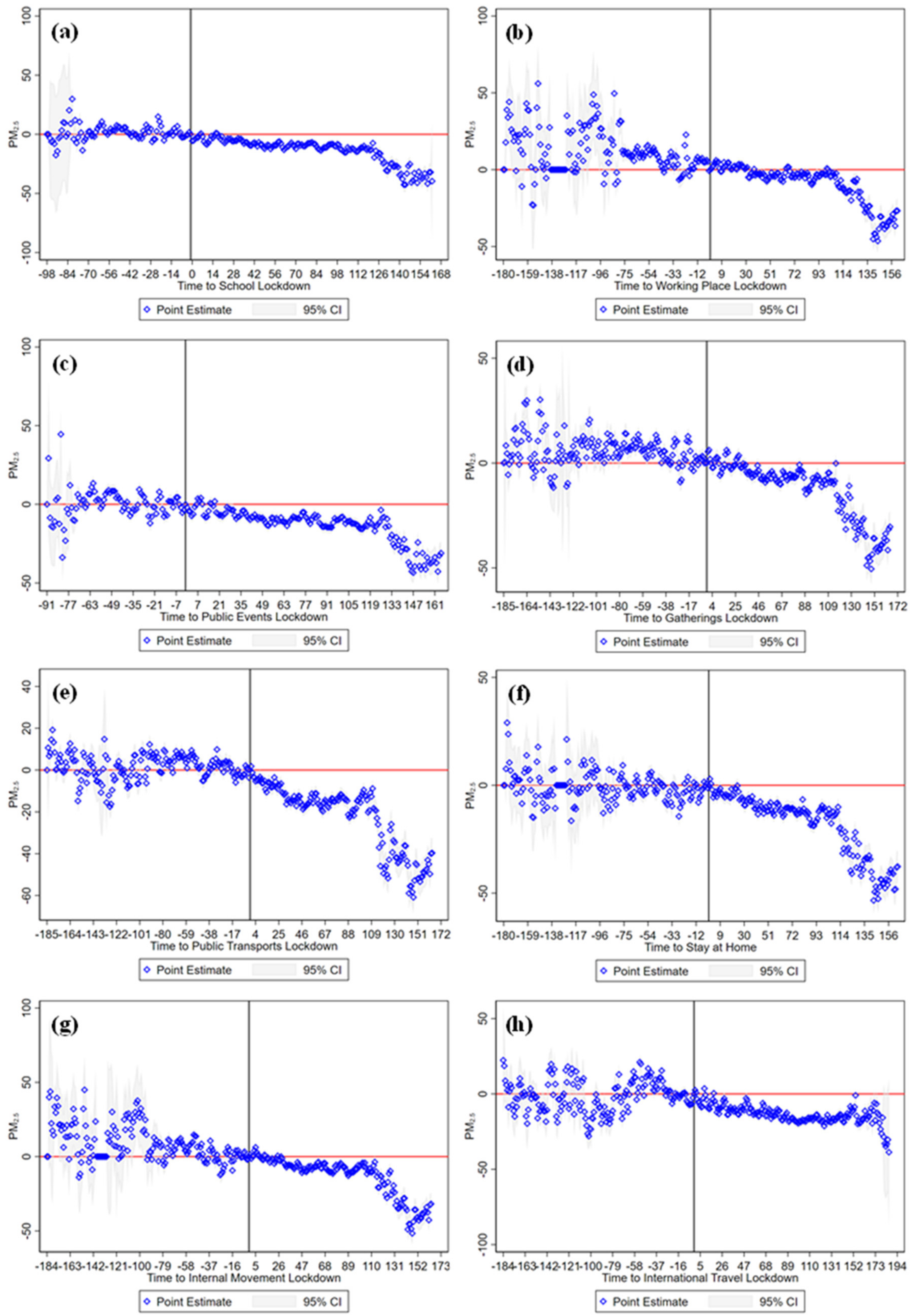

Fig. 5. Event-study results on $PM_{2.5}$. *Notes*: These figures summarize the results of the parallel trend tests based on Eq. (4). 95% confidence bands. The solid black line indicates the date of one day before the enforcement of lockdown measures; its corresponding dummy variable is omitted from the specifications.

Table 3
The effects of lockdown on air pollution: $PM_{2.5}$.

Lockdown measures	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	C1	C2	C3	C4	C5	C6	C7	C8
T_Lockdown	-2.458^{***}	-2.299^{***}	-3.568^{***}	-1.357^{***}	-7.234^{***}	-3.023^{***}	-2.692^{***}	-2.728^{***}
	(0.088)	(0.100)	(0.136)	(0.071)	(0.178)	(0.117)	(0.130)	(0.084)
Humidity	-0.026^{***}	-0.023^{***}	-0.027^{***}	-0.018^{***}	-0.017^{***}	-0.023^{***}	-0.023^{***}	-0.033^{***}
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Temperature	-0.802^{***}	-0.839^{***}	-0.796^{***}	-0.862^{***}	-0.789^{***}	-0.867^{***}	-0.873^{***}	-0.765^{***}
	(0.016)	(0.016)	(0.017)	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)
Wind_speed	-0.296^{***}	-0.300^{***}	-0.305^{***}	-0.302^{***}	-0.301^{***}	-0.300^{***}	-0.303^{***}	-0.301^{***}
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
R^2(within)	0.847	0.846	0.847	0.846	0.849	0.847	0.846	0.847
No. of cities	597	597	597	597	597	597	597	597
No. of countries	76	76	76	76	76	76	76	76
N	71,305	71,423	71,331	71,423	71,438	71,439	71,384	71,419
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City by Date Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country by Date Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses are clustered at the city-day level. Stars denote significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

response index is associated with reductions in six air pollutants, which is consistent with our baseline results.

Combining these two sets of results, the changes in air quality in the treatment group relative to the control group indicates that cities enforcing lockdown measures experience a clearly larger reduction in local air pollution. This finding is consistent with our expectation that cities would experience a considerably lower air pollution level than those experienced in normal conditions due to the lockdown-induced dramatical decrease in industrial activities and vehicle use. Furthermore, the pollution abatement effect is more significant in terms of NO_2. In terms of different lockdown measures, intra/intercity travel restrictions still have a better performance in improving air quality.

4.3. Robustness checks

In this section, we check whether the main results of our study are robust to data and empirical strategies. First, we use the stringency index that directly reflects the stringency of containment policies to replace the ordinal indicators that represent the level of strictness of different lockdown measures as the key independent variable in Eq. (1) and re-estimate the models. Second, we take the log of air pollution index value as the dependent variables and re-estimate Eq. (2) as log transformation is capable of reducing the influence of outliers. Third, considering that the incubation period of COVID-19 is somewhere between 2 and 14 days after exposure (Lauer et al., 2020; CDC, 2020), the restrictions would be stricter within 14 days after the enforcement of lockdown measures hence the lockdown effect on cities' air quality will be more significant. We use a shorter post-lockdown period to rule out these disturbing factors. Fourth, considering that only one monitoring stations' readings are available in some cities, which may not be the representative of the air quality of the entire city. We exclude those cities and re-estimate Eq. (2). Finally, we check whether our results are sensitive to the specified estimation strategy. We use a dynamic panel data model to identify the causal effect of counter-COVID-19 measures on air quality. In general, we find that estimates are similar in sign and magnitude to those in Tables 4 and 5. This provides supportive evidence for our baseline results. We provide the results of the robustness check using $PM_{2.5}$ in Table 7; the results for the other five air pollutants are still remarkably robust to alternative specifications, which are not reported here due to the limit of space and are available upon request.

Table 4
The effects of lockdown on air pollution using different air pollutants.

Lockdown measures	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	C1	C2	C3	C4	C5	C6	C7	C8
Panel A: $PM_{2.5}$	-2.458^{***}	-2.299^{***}	-3.568^{***}	-1.357^{***}	-7.234^{***}	-3.023^{***}	-2.692^{***}	-2.728^{***}
	(0.088)	(0.100)	(0.136)	(0.071)	(0.178)	(0.117)	(0.130)	(0.084)
Panel B: PM_{10}	-1.804^{***}	-2.130^{***}	-2.696^{***}	-1.264^{***}	-4.291^{***}	-2.286^{***}	-2.342^{***}	-1.529^{***}
	(0.055)	(0.064)	(0.084)	(0.044)	(0.107)	(0.071)	(0.081)	(0.051)
Panel C: SO_2	-0.286^{***}	-0.328^{***}	-0.489^{***}	-0.070^{***}	-0.385^{***}	-0.292^{***}	-0.452^{***}	-0.077^{***}
	(0.021)	(0.025)	(0.033)	(0.017)	(0.039)	(0.027)	(0.031)	(0.020)
Panel D: NO_2	-1.404^{***}	-1.601^{***}	-2.175^{***}	-0.946^{***}	-2.331^{***}	-1.532^{***}	-1.779^{***}	-0.956^{***}
	(0.016)	(0.019)	(0.025)	(0.013)	(0.032)	(0.022)	(0.024)	(0.016)
Panel E: CO	-0.237^{***}	-0.258^{***}	-0.326^{***}	-0.118^{***}	-0.433^{***}	-0.293^{***}	-0.290^{***}	-0.219^{***}
	(0.022)	(0.025)	(0.035)	(0.018)	(0.043)	(0.029)	(0.033)	(0.021)
Panel F: O_3	1.544^{***}	1.495^{***}	2.258^{***}	0.877^{***}	1.443^{***}	1.525^{***}	1.561^{***}	1.249^{***}
	(0.025)	(0.029)	(0.039)	(0.020)	(0.051)	(0.033)	(0.037)	(0.024)
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City by Date Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country by Date Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses are clustered at the city-day level. Stars denote significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Panel A to F reports the regression results based on Eq. (1) with $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, and O_3 as the dependent variable. Weather controls include temperature, humidity, and wind speed.

Table 5
The effects of lockdown on air pollution: DID estimates.

Lockdown measures	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	C1	C2	C3	C4	C5	C6	C7	C8
Panel A: $PM_{2.5}$	-7.688^{***}	-7.137^{***}	-6.628^{***}	-6.025^{***}	-7.352^{***}	-3.669^{***}	-4.998^{***}	-9.610^{***}
	(0.261)	(0.247)	(0.262)	(0.260)	(0.257)	(0.240)	(0.236)	(0.290)
Panel B: PM_{10}	-5.469^{***}	-5.227^{***}	-4.939^{***}	-4.872^{***}	-5.035^{***}	-3.272^{***}	-4.027^{***}	-5.271^{***}
	(0.160)	(0.150)	(0.161)	(0.160)	(0.153)	(0.144)	(0.142)	(0.178)
Panel C: SO_2	-0.860^{***}	-0.846^{***}	-0.901^{***}	-0.421^{***}	-0.709^{***}	-0.601^{***}	-0.761^{***}	-0.119^{*}
	(0.062)	(0.058)	(0.062)	(0.062)	(0.058)	(0.055)	(0.055)	(0.069)
Panel D: NO_2	-4.144^{***}	-3.795^{***}	-4.160^{***}	-3.355^{***}	-3.365^{***}	-2.965^{***}	-3.143^{***}	-2.670^{***}
	(0.048)	(0.045)	(0.048)	(0.049)	(0.046)	(0.043)	(0.043)	(0.055)
Panel E: CO	-0.724^{***}	-0.678^{***}	-0.659^{***}	-0.462^{***}	-0.472^{***}	-0.407^{***}	-0.531^{***}	-0.700^{***}
	(0.071)	(0.066)	(0.071)	(0.070)	(0.067)	(0.065)	(0.063)	(0.078)
Panel F: O_3	4.202^{***}	3.807^{***}	4.488^{***}	2.814^{***}	2.024^{***}	3.182^{***}	3.128^{***}	3.677^{***}
	(0.076)	(0.071)	(0.076)	(0.077)	(0.073)	(0.067)	(0.067)	(0.084)
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City by Date Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country by Date Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses are clustered at the city-day level. Stars denote significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Panel A to F reports the regression results based on Eq. (2) with $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, and O_3 as the dependent variable. Weather controls include temperature, humidity, and wind speed.

Interestingly, in column (3) of Table 7, we observe that the sub-sample estimates are considerably smaller in magnitude than estimates in Table 5. It suggests that lockdown measures may have a cumulative effect on the air pollution abatement, that is it will take time to see the dispersion of air pollutants as economies ground to a near halt. Thus, the environmental effects of lockdown measures may be marginal in the period immediately after the launch of these policies.

4.4. Heterogeneity

As the focus of this study is on the global air quality changes during the pandemic caused by lockdown measures, it is necessary to examine whether there is any evidence of heterogeneous effects of a specific lockdown measure. Given the data availability, we use the socio-economic data at the country-level for the classification of different cities. We first examine how the air pollution reduction effect differs by level of development, column (1) and (2) of Table 8 present separate regressions for high/low per capita GDP (*PGDP*) cities. Then we examine how the lockdown effect differs between large/small population (*Popu*) cities in column (3) and (4), and cities that rely more on industrial production (measured by the share of secondary production (*Manu*) and carbon dioxide emissions (CO_2) in columns (5) to (8). According to those indicators, we divide cities into different subgroups; for instance, if a city's per capita GDP is higher than the mean value, it will fall into a “high” group, otherwise the “low” group.

The results in Table 8 are very similar and do not differ significantly from the baseline results. We also find significant heterogeneity in the lockdown effect, cities from countries with a lower income level and larger population experience a larger reduction in air pollution level during the sample period. This finding is consistent with the fact that most high-income countries in our sample tend to have a relatively

Table 6
The effects of lockdown on air pollution: Government response index-based DID estimates.

Independent variable: $GRI_{mit} \times T\_Lockdown^{n}_{mit}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	C1	C2	C3	C4	C5	C6	C7	C8
Panel A: $PM_{2.5}$	-0.121^{***}	-0.111^{***}	-0.119^{***}	-0.107^{***}	-0.171^{***}	-0.105^{***}	-0.107^{***}	-0.161^{***}
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Panel B: PM_{10}	-0.090^{***}	-0.084^{***}	-0.089^{***}	-0.081^{***}	-0.110^{***}	-0.080^{***}	-0.082^{***}	-0.097^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Panel C: SO_2	-0.011^{***}	-0.011^{***}	-0.011^{***}	-0.007^{***}	-0.014^{***}	-0.011^{***}	-0.010^{***}	-0.005^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Panel D: NO_2	-0.064^{***}	-0.061^{***}	-0.066^{***}	-0.058^{***}	-0.064^{***}	-0.060^{***}	-0.062^{***}	-0.055^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Panel E: CO	-0.011^{***}	-0.010^{***}	-0.011^{***}	-0.006^{***}	-0.012^{***}	-0.010^{***}	-0.010^{***}	-0.012^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Panel F: O_3	0.062^{***}	0.058^{***}	0.062^{***}	0.052^{***}	0.044^{***}	0.058^{***}	0.057^{***}	0.062^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City by Date Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country by Date Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses are clustered at the city-day level. Stars denote significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Panel A to F reports the regression results based on Eq. (3) with $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, and O_3 as the dependent variable. Weather controls include temperature, humidity, and wind speed.

Table 7
Robustness test: $PM_{2.5}$.

	(1)	(2)	(3)	(4)	(5)
	Stringency index	log ($PM_{2.5}$)	14 days after each of the lockdown dates only	Cities with more than one monitoring stations only	The dynamic panel data model
$PM_{2.5}$	-0.116^{***}				
	(0.004)				
C1		-0.096^{***}	-6.673^{***}	-7.217^{***}	-2.684^{***}
		−0.005	(0.428)	(0.263)	(0.202)
C2		-0.090^{***}	-4.529^{***}	-6.765^{***}	-2.412^{***}
		−0.004	(0.426)	(0.248)	(0.190)
C3		-0.082^{***}	-5.974^{***}	-6.118^{***}	-2.401^{***}
		−0.005	(0.446)	(0.264)	(0.202)
C4		-0.082^{***}	-6.580^{***}	-5.570^{***}	-2.014^{***}
		−0.005	(0.414)	(0.263)	(0.200)
C5		-0.104^{***}	-5.807^{***}	-6.883^{***}	-2.719^{***}
		−0.005	(0.411)	(0.260)	(0.198)
C6		-0.035^{***}	-3.365^{***}	-3.177^{***}	-1.369^{***}
		−0.004	(0.393)	(0.241)	(0.183)
C7		-0.051^{***}	-3.353^{***}	-4.533^{***}	-1.744^{***}
		−0.004	(0.435)	(0.238)	(0.181)
C8		-0.132^{***}	-6.717^{***}	-9.325^{***}	-3.504^{***}
		−0.005	(0.486)	(0.291)	(0.223)

Notes: Column (1) to (5) reports the estimates with the stringency index as the independent variable based on Eq. (1), log($PM_{2.5}$) as the dependent variable based on Eq. (2), a sub-sample analysis based on Eq. (2) that including 14 days after the enforcement of lockdown measures only, a sub-sample analysis after excluding cities with only one monitoring stations based on Eq. (2), and an alternative specification by a dynamic panel data model, respectively. The date, city, and country fixed effects are included in all specifications. The city-specific and country-specific linear time trends are included in all columns. Weather controls include temperature, humidity, and wind speed. Standard errors in parentheses are clustered at the city-day level. Significance level: ***, **, and * denotes significance at the 1%, 5%, and 10% levels, respectively.

low level of air pollution during the pre-lockdown period, so do major cities in these countries. Thus, the space for further reduction in air pollution is limited. At the same time, the effect becomes more substantial for cities from countries with a larger population, indicating that more agglomerated economies consume more energy. Columns (5) to (8) show that cities that rely more on industrial activities experience a more significant effect, suggesting that industrial activities are an essential source of air pollution.

4.5. Health implications of lockdown measures

A large number of researches has confirmed the link between high levels of air pollutants and deteriorating health, in both developed countries (Lavaine and Neidell, 2017; Deryugina et al., 2019) and developing countries (Ebenstein et al., 2017; Fan et al., 2020). Here, we present a brief analysis on the health benefits from the air improvement during the lockdown. Given the data availability, the associated country-level health-related variables are used for the prediction of health benefits here. We refer to the research of He et al. (2016) to predict the reduced mortality out of the air quality improvement:

$$Mortality_m = \Delta AQL_m \times RR \times BaseMR_m \times Popu_m \tag{5}$$

where $Mortality_m$ indicates the estimated saved deaths of country m during the sample period. ΔAQL_m represents the estimated change in air quality level (measured by the concentrations of $PM_{2.5}$ here) in country m during the sample period. We first calculate the elasticity of air quality to the stringency index through Eq. (1), then this elasticity is multiplied by the accumulative change of stringency index during the sample period. Since the calculating results here represent the individual pollutant AQI value, we convert them to the concentration value based on the AQI Calculator provided by the World Air Quality Index project team. *RR* represents the sensitivity of mortality to a one-unit change in air pollution level since its estimate is not the focus of interest in this study, we use the estimates from existing researches on the effect of air pollution on human health. Since the impacts of air pollution on human health vary over time, researches of this filed based on data from earlier years may be less effective as the reference. Moreover, considering the credit of estimates based on quasi-experimental studies compared with those based on associated regression models (Graff Zivin and Neidell, 2013). We used Web of Science, Google Scholar, Scopus, and other databases to identify academic articles and book chapters that meet these criteria, and it could be found that eligible articles in this field are not that rich. Finally, Fan et al. (2020) who, through a Regression Discontinuity (RD) analysis, found that a 10-μg/m^3 increase in $PM_{2.5}$ resulted in a 2.2% increase in mortality rate; and He et al. (2020) who proposed that this rate can reach over 3.25% through an estimation of the effect of straw burning on air pollution and health are chosen as two main references. We are assuming that the cause-specific coefficient (*RR*) in China is a representative one, thus 2.2%– 3.25% increase in mortality following a 10-μg/m^3 increase in $PM_{2.5}$ is applicable to the

Table 8
The heterogeneous impacts of lockdown using PM2.5.

Dependent variable: $PM_{2.5}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PGDP_H	PGDP_L	Popu_H	Popu_L	Manu_H	Manu_L	CO_2_H	CO_2_L
C1	-4.078^{***}	-17.327^{***}	-11.116^{***}	-6.008^{***}	-11.224^{***}	-5.609^{***}	-10.789^{***}	-4.099^{***}
	(0.242)	(0.503)	(0.483)	(0.303)	(0.420)	(0.292)	(0.424)	(0.358)
C2	-3.586^{***}	-16.088^{***}	-10.457^{***}	-4.945^{***}	-11.480^{***}	-4.868^{***}	-9.695^{***}	-3.893^{***}
	(0.222)	(0.496)	(0.420)	(0.301)	(0.387)	(0.285)	(0.372)	(0.358)
C3	-2.733^{***}	-17.081^{***}	-10.407^{***}	-4.867^{***}	-9.092^{***}	-5.641^{***}	-9.480^{***}	-4.913^{***}
	(0.241)	(0.515)	(0.499)	(0.301)	(0.422)	(0.294)	(0.429)	(0.366)
C4	-2.883^{***}	-14.675^{***}	-14.067^{***}	-2.489^{***}	-10.711^{***}	-4.374^{***}	-9.163^{***}	-2.464^{***}
	(0.240)	(0.508)	(0.515)	(0.292)	(0.431)	(0.286)	(0.408)	(0.374)
C5	−0.241	-14.606^{***}	-11.358^{***}	-4.522^{***}	-15.801^{***}	-0.623^{**}	-10.014^{***}	-6.361^{***}
	(0.257)	(0.447)	(0.426)	(0.319)	(0.416)	(0.284)	(0.392)	(0.383)
C6	-1.293^{***}	-10.552^{***}	-5.793^{***}	-2.478^{***}	-6.731^{***}	-2.331^{***}	-4.602^{***}	-2.566^{***}
	(0.212)	(0.495)	(0.443)	(0.278)	(0.382)	(0.271)	(0.375)	(0.341)
C7	-1.063^{***}	-14.366^{***}	-9.494^{***}	-2.228^{***}	-8.545^{***}	-3.447^{***}	-7.179^{***}	-2.792^{***}
	(0.207)	(0.489)	(0.415)	(0.280)	(0.371)	(0.271)	(0.359)	(0.340)
C8	-5.556^{***}	-15.909^{***}	-20.502^{***}	-4.440^{***}	-15.125^{***}	-4.883^{***}	-18.969^{***}	-3.314^{***}
	(0.269)	(0.548)	(0.550)	(0.330)	(0.478)	(0.313)	(0.472)	(0.396)

Notes: The date, city, and country fixed effects are included in all specifications. The city-specific and country-specific linear time trends are included in all columns. Weather controls include temperature, humidity, and wind speed. Standard errors in parentheses are clustered at the city-day level. Significance level: ***, **, and * denotes significance at the 1%, 5%, and 10% levels, respectively. The socio-economic data involved in this table for the classification are measured at 2016 as the base year, per capita GDP, population, and carbon dioxide emissions are all collected from the WDI dataset of World Bank, and the indicator regarding the share of industry is collected from the UNCTAD dataset. We use "_H" and "_L" to represent the "high" group and the "low" group, respectively. All specifications are based on Eq. (2).

whole world. $BaseMR_m$ denotes the annual mortality related to air pollution in country m at the base year, and $Popu_m$ indicates the population in country m at the base year. Given the data availability, we set 2016 as the base year of mortality rate and population, both of them are collected from The WHO Global Health Estimates.[9]

The results show that the total number of averted premature deaths related to air pollution is around 99,270 to 146,649 attributable to governments' lockdown measures during the sample period among countries in our sample. The highest reductions occurred for India (29,546–43,647), followed by China (29,413–43,450) and Indonesia (4427–6540).[10] These results reflect the enormous social costs out of air pollution worldwide during the normal times. It is important to notice that this calculation is based on a set of assumptions. First, we are assuming that the cause-specific coefficient of concentration-response functions is fixed i.e. a 10-μg/m^3 decrease in concentrations would double the mortality effect of a 5-μg/m^3 reduction. Second, following Cole et al. (2020), we are assuming that any other potential mortality effects due to lockdowns, such as more exposure to indoor pollution and reduced road accidents, are negligible. Last, this back-of-the-envelope calculation is based on a single pollutant, $PM_{2.5}$, there remains some uncertainty if health benefits of different pollutants are independent of each other. Nevertheless, this calculation suggests that the improved air quality caused by lockdowns results in significant reductions in mortality worldwide.

5. Conclusion and discussion

With the spread of COVID-19 around the world, the widespread and rapid governments' responses have resulted in sweeping impacts. Among these, air quality impacts might be expected to experience a dramatic improvement worldwide. This paper quantifies the causal impact of various lockdown measures on the air quality (measured by $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, and O_3 individual AQI) in 597 major cities from 76 countries and regions using a novel COVID-19 government response tracker dataset, combining a research data platform that gathers, harmonizes, and links the worldwide air pollution data and weather data from January 1, 2020 to July 5, 2020. Based on these, a fixed-effects OLS specification and two sets of DID analyses are conducted. This pandemic allows us to examine the relative changes in air quality to that during the normal times through a “largest scale experiment ever” from COVID-19 responses. We find that different air pollutants respond quite differently to the lockdown measures. While the NO_2 individual AQI falls more precipitously (23–37%) than the other five air pollutants during the sample period, followed by PM_{10} (14–20%), SO_2 (2–20%), $PM_{2.5}$ (7–16%), and CO (7–11%) relative to the threshold. In contrast, the ozone individual AQI increase by 10–27%. With regard to different lockdown measures, intra/intercity travel restrictions have a better performance in curbing air pollution. These results are robust to different specifications, including different sample sizes, different estimation strategies, and different independent variables. We then combine the estimated reductions in air pollution level with expected health benefits and find that the reductions in emissions caused by the pandemic-induced lockdown measures reduced premature deaths by around 99,270 to 146,649 among countries and regions in our study during the sample period.

The results of this study have the potential to provide useful information regarding the further costs and benefits of different air pollution control strategies in the post-pandemic period. Moreover, this analysis adds to the literature identifying lockdown-related impacts on air pollution and associated health benefits, and more generally on changes in air quality associated with specific causes. Future studies may expand on these areas and address additional confounders such as meteorological trends, pre-lockdown environmental regulations, and national differences to shed light on the extent to which the observed changes in air pollution are attributable to pandemic-induced lockdown measures. Additional work could also identify the specific health benefits from the lockdown-induced changes in the air pollution level, particularly from a long-term perspective. Moreover, the difference in different air pollutants' response to the coronavirus outbreak and the specific mechanisms also need further analysis.

[9] More information about the assessment of mortality can be found at https://www.who.int/healthinfo/global_burden_disease/en/.

[10] The full results are not reported here due to the limit of space, which are available upon request.

CRediT authorship contribution statement

Feng Liu: Writing - original draft, Conceptualization, Methodology. **Meichang Wang:** Writing - original draft, Data curation, Software. **Meina Zheng:** Writing - review & editing, Visualization.

Declaration of competing interest

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

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Appendix A. Supplementary data

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References

Beaudoin, J., Lin Lawell, C.-Y.C., 2016. Is public transit's “green” reputation deserved?: evaluating the effects of transit supply on air quality. [Working paper]. http://www.des.ucdavis.edu/faculty/Lin/transit_airquality_paper.pdf.
Callaway, B., Sant'Anna, P.H.C., 2018. Difference-in-differences with multiple time periods. SSRN https://doi.org/10.2139/ssrn.3148250.
Centers for Disease Control and Prevention (CDC), 2020. Symptoms of coronavirus. https://www.cdc.gov/coronavirus/2019-ncov/about/symptoms.html. (Accessed 25 June 2020).
Chan, J.F.-W., Yuan, S., Kok, K.-H., To, K.K.-W., Chu, H., et al., 2020. A familial cluster of pneumonia associated with the 2019 novel coronavirus indicating person-to-person transmission: a study of a family cluster. Lancet 395, 514–523. https://doi.org/10.1016/S0140-6736(20)30154-9.
Cole, M., Elliott, R., Liu, B., 2020. The Impact of the Wuhan Covid-19 Lockdown on Air Pollution and Health: A Machine Learning and Augmented Synthetic Control Approach. Discussion Papers from Department of Economics, University of Birmingham https://econpapers.repec.org/paper/birbirmec/20-09.htm.
Correia, S., Luck, S., Verner, E., 2020. Pandemics depress the economy, public health interventions do not: evidence from the 1918 flu. SSRN https://doi.org/10.2139/ssrn.3561560.
Deryugina, T., Heutel, G., Miller, N.H., Molitor, D., Reif, J., 2019. The mortality and medical costs of air pollution: evidence from changes in wind direction. Am. Econ. Rev. 109, 4178–4219. https://doi.org/10.1257/aer.20180279.
Deschênes, O., Greenstone, M., Shapiro, J.S., 2017. Defensive investments and the demand for air quality: evidence from the NOx budget program. Am. Econ. Rev. 107, 2958–2989. https://doi.org/10.1257/aer.20131002.
Ebenstein, A., Fan, M., Greenstone, M., He, G., Zhou, M., 2017. New evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai river policy. Proc. Natl. Acad. Sci. 110, 12936–12941. https://doi.org/10.1073/pnas.1616784114.
Fan, M., He, G., Zhou, M., 2020. The winter choke: coal-fired heating, air pollution, and mortality in China. J. Health Econ. 71, 102316. https://doi.org/10.1016/j.jhealeco.2020.102316.
Gendron-Carrier, N., Gonzalez-Navarro, M., Polloni, S., Turner, M.A., 2018. Subways and Urban Air Pollution. NBER Working Papers No. 24183. https://doi.org/10.3386/w24183.
Goodman-Bacon, A., Marcus, J., 2020. Using Difference-in-differences to Identify Causal Effects of COVID-19 Policies. Discussion Papers of DIW Berlin 1870. German Institute for Economic Research, DIW Berlin https://ideas.repec.org/p/diw/diwwpp/dp1870.html.

Graff Zivin, J., Neidell, M., 2013. Environment, health, and human capital. J. Econ. Lit. 51, 689–730. https://doi.org/10.1257/jel.51.3.689.
Hale, T., Webster, S., Petherick, A., Phillips, T., Kira, B., 2020. Oxford COVID-19 Government Response Tracker. Blavatnik School of Government https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker#data.
He, G., Fan, M., Zhou, M., 2016. The effect of air pollution on mortality in China: evidence from the 2008 Beijing Olympic Games. J. Environ. Econ. Manag. 79, 18–39. https://doi.org/10.1016/j.jeem.2016.04.004.
He, G., Liu, T., Zhou, M., 2020. Straw burning, $PM_{2.5}$, and death: evidence from China. J. Dev. Econ. 145, 102468. https://doi.org/10.1016/j.jdeveco.2020.102468.
Lauer, S.A., Grantz, K.H., Bi, Q., Jones, F.K., Zheng, Q., Meredith, H.R., Azman, A.S., Reich, N.G., Lessler, J., 2020. The incubation period of coronavirus disease 2019 (COVID-19) from publicly reported confirmed cases: estimation and application. Ann. Intern. Med. 172, 577–582. https://doi.org/10.7326/M20-0504.
Lavaine, E., Neidell, M., 2017. Energy production and health externalities: evidence from oil refinery strikes in France. J. Assoc. Environ. Resour. Econ. 4, 447–477. https://doi.org/10.1086/691554.
Li, L., Li, Q., Huang, L., Wang, Q., Zhu, A., et al., 2020. Air quality changes during the COVID-19 lockdown over the Yangtze River Delta Region: an insight into the impact of human activity pattern changes on air pollution variation. Sci. Total Environ. 732, 139282. https://doi.org/10.1016/j.scitotenv.2020.139282.
Rivers, N., Saberian, S., Schaufele, B., 2020. Public transit and air pollution: evidence from Canadian transit strikes. Can. J. Econ.-Rev. Can. Econ. 53, 496–525. https://doi.org/10.1111/caje.12435.
Sharma, S., Zhang, M., Anshika Gao, J., Kota, S.H., 2020. Effect of restricted emissions during COVID-19 on air quality in India. Sci. Total Environ. 728, 138878. https://doi.org/10.1016/j.scitotenv.2020.138878.
Tobías, A., 2020. Evaluation of the lockdowns for the SARS-CoV-2 epidemic in Italy and Spain after one month follow up. Sci. Total Environ. 725, 138539. https://doi.org/10.1016/j.scitotenv.2020.138539.
Venter, Z.S., Aunan, K., Chowdhury, S., Lelieveld, J., 2020. COVID-19 lockdowns cause global air pollution declines. PNAS 117 (32), 18984–18990. https://doi.org/10.1073/pnas.2006853117.
Watts, J., Kommenda, N., 2020. Coronavirus pandemic leading to huge drop in air pollution. https://www.theguardian.com/environment/2020/mar/23/coronavirus-pandemic-leading-to-huge-drop-in-air-pollution. (Accessed 23 March 2020).
World Health Organization (WHO), 2020. WHO coronavirus disease (COVID-19) dashboard. https://covid19.who.int/. (Accessed 7 July 2020).