nature sustainability

ARTICLES

https://doi.org/10.1038/s41893-020-0581-y

The short-term impacts of COVID-19 lockdown on urban air pollution in China

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To prevent the escalation of COVID-19 transmission, China locked down one-third of its cities, which strictly curtailed personal mobility and economic activities. Using comprehensive daily air quality data in China, we evaluated the impacts of these measures in terms of the Air Quality Index (AQI) and the concentrations of particulate matter with a diameter of less than 2.5 μm ($PM_{2.5}$). To infer their causal relationships, we employed difference-in-differences models that compare cities with and without lockdown policies. We found that city lockdowns led to a sizeable improvement in air quality. Within weeks, the AQI in the locked-down cities was brought down by 19.84 points ($PM_{2.5}$ down by 14.07 μg m^{-3}) relative to the control group. In addition, air quality in cities without formal lockdowns also improved because of the enforcement of other types of counter-virus measures. The AQI in those cities was brought down by 6.34 points ($PM_{2.5}$ down by 7.05 μg m^{-3}) relative to the previous year. The lockdown effects are larger in colder, richer and more industrialized cities. Despite these improvements, $PM_{2.5}$ concentrations during the lockdown periods remained four times higher than the World Health Organization recommendations, suggesting much further effort is needed. Existing environmental policies could obtain similar air quality improvements at a much lower economic cost, making city lockdowns an unsustainable option to address environmental issues.

The rapid spread of COVID-19 has become a global public health crisis. In December 2019, an unknown disease, later named COVID-19, was detected in Wuhan, China[1,2]. Within five months, the disease had affected more than 210 countries, becoming a global pandemic and bringing devastating consequences[3,4]. To contain the virus, many countries have adopted dramatic measures to reduce human interaction, including enforcing strict quarantines, prohibiting large-scale private and public gatherings, restricting private and public transportation, encouraging social distancing, imposing a curfew and even locking down entire cities.

Although the costs of enforcing these preventive measures are undoubtedly enormous, these measures could unintentionally bring about substantial social benefits. Among them, locking down cities could considerably improve environmental quality, which would partially offset the costs of these counter-COVID-19 measures. For example, satellite images captured a sharp drop in air pollution in several countries that have taken aggressive measures to slow transmission of the virus[5–8].

In this study, we estimated how lockdown affected air quality across China's cities. We focused on China for two reasons. First, it was the first country struck by the outbreak, and the Chinese government launched draconian countermeasures to prevent the escalation of infections[9,10]. Nearly one-third of Chinese cities were locked down in a top-down manner, and various types of economic activity were strictly prohibited. In these cities, individuals were required to stay at home; unnecessary commercial operations and private and public gatherings were suspended; all forms of transportation were largely banned (both within a city and across cities); and mandatory temperature checking was introduced in most public facilities. Second, China also suffers greatly from severe air pollution, with some estimates suggesting that air pollution is associated with an annual loss of nearly 25 million healthy life years[11]. If locking down cities substantially improved the air quality in China, the implied health benefits would be an order of magnitude larger than in countries with lower initial pollution levels.

Our empirical analysis used comprehensive data at a day-by-city level from January 1st to March 1st in 2020. We first collected air quality data from 1,600 monitoring stations covering all the prefectural cities in China and aggregated the station-level data to the city-level data (see Methods and Supplementary Table 1). We then collected the local government's lockdown policies city by city from news media and government announcements. Because the disease prevalence varied greatly across different regions, the terms and requirements of the lockdown also differed across provinces and cities. Thus, we defined a city as locked down when all three of the following preventive measures were enforced: (1) prohibition of unnecessary commercial activities in people's daily lives; (2) prohibition of any types of gathering by residents; (3) restrictions on private (vehicle) and public transportation. Following our definition, 95 out of 324 cities were locked down, as described in Figs. 1 and 2 and Supplementary Table 2. We also provide the summary statistics of the key variables in Supplementary Table 3 and discuss the trends in air pollution in Supplementary Note 1 and Supplementary Fig. 1.

To quantify the impact of the city lockdown on air pollution, we employed two sets of difference-in-differences (DiD) models (see Methods). The DiD models allow us to control for various confounding factors that potentially affect the air pollution level, and to identify the plausible causal impact of virus containment measures. To assess the overall impact of city lockdowns relative to the previous year, we estimated two policy effects: (1) how city lockdown improves air quality relative to non-locked-down cities in 2020, and (2) how national-level disease preventive measures (for example, all cities extended the Spring Festival holiday, required social distancing and urged people to stay at home) affect air pollution in non-locked-down cities relative to trends in the previous years.

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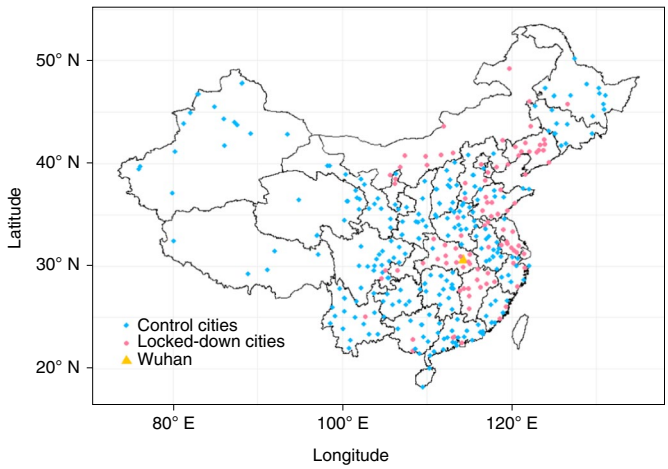

Fig. 1 | Map of the locked-down cities. The 95 cities that were locked down during the COVID-19 pandemic are shown, as are the rest of the 324 cities included as controls.

Our comprehensive dataset and statistical methods have some notable advantages for inferring the causal relationship between city lockdowns and air quality. First, although there is much anecdotal evidence to suggest that air quality improved after the COVID-19 outbreak, this often relies on comparing air pollution levels before and after the outbreak[5–8]. The before–after comparison can be problematic because it lacks a proper counterfactual. In the Chinese setting, this becomes more of a concern: the air pollution levels have been declining in most cities over the last several years owing to the government's environmental regulations. The spread of the virus also coincided with the Chinese Spring Festival. As a result, the before–after comparison could simply capture the declining trend in air pollution caused by the regulation or the national holiday. Our DiD strategy helps to address this issue because cities without lockdown policies can serve as the counterfactual, mimicking what would happen in lockdown cities in the absence of its implementation. Second, a key empirical challenge in many single-city and single-region studies is that pollution changes in a specific location could be caused by unobserved shocks specific to that location. Our large sample helps to address this challenge: it allows us to control for city-specific time-invariant characteristics and plausibly estimate the average effect of city lockdowns in all Chinese cities.

The comprehensive dataset further helps us to examine whether the effects of lockdowns vary across different types of city, which sheds light on different sources of air pollution in China. For example, we expected that more industrialized cities could be more substantially influenced by such treatments because industrial activities are largely suspended. Similarly, we also expected that colder cities (which have higher coal demand for winter heating), richer cities (which have higher electricity consumption) or cities with higher traffic volumes might experience a more substantial reduction in air pollution when the lockdown is implemented.

Finally, our findings provide an important perspective from which to understand the welfare implications of COVID-19 and offer insights on how to better design environmental policies. We will discuss these policy-relevant issues in the Discussion.

Results

Impacts of city lockdowns on air pollution. We estimated the relative change in air pollution levels in the treatment group (locked-down cities) relative to the control group (non-locked-down cities) by fitting the DiD model (Table 1 and equation (1)). We find that the lockdown did improve air quality: compared with cities without formal lockdown policies, the daily AQI and $PM_{2.5}$ declined respectively by 19.84 points (17%) and 14.07 μg m^{-3} (17%) when including weather controls and a set of fixed effects (in columns (2) and (4)). These estimates are remarkably robust to the inclusion of weather variables, indicating that the changes in air pollution caused by city lockdown are unlikely to be correlated with weather conditions. We also provide the results for other air pollutants in Supplementary Table A4 (CO, NO_2, PM_{10}, SO_2, O_3) and find that city lockdown reduces all pollutants but ozone (O_3). This is probably because the reduction in NO (nitric oxide) slows down its interaction with O_3 and consequently the O_3 concentration increases[12,13].

Even in a city that did not have a formal lockdown policy, air quality level may be affected by disease preventive measures such as the extension of the Spring Festival holiday, the stay at home order and the social distancing policy. Therefore, in columns (5) to (8), we estimate the changes in air pollution levels in the control cities before and after the start of the Spring Festival (25 January) relative to the previous year by fitting the second DiD model (see equation (3)). We find that air quality in 2020 improved relative to the previous year's air quality after the start of the festival. The results show that the AQI decreases by 6.34 points (5%) and $PM_{2.5}$ by 7.05 μg m^{-3} (7%) after controlling for weather variables (columns (6) and (8)), suggesting that the disease preventive measures matter for air quality in cities even without formal lockdown.

Our first DiD measures how the city lockdown improves air quality relative to non-locked-down cities in 2020, and the second DiD assesses how national-level disease preventive measures affect non-locked-down cities relative to the same season in previous years. Combining these two sets of results, we can estimate the overall effects of city lockdowns on air quality. We find that lockdown improved air quality substantially: it reduced AQI by 26.18 points (19.84 points from the first DiD and 6.34 points from the second DiD), which corresponds to a 22% reduction; $PM_{2.5}$ was brought down by 21.12 μg m^{-3} (14.07 μg m^{-3} from the first DiD and 7.05 μg m^{-3} from the second DiD), which corresponds to a 24% reduction.

Tests for pre-treatment parallel trends and additional analyses. We adopted the event study approach to investigate how the trends in air quality between the treatment and control groups evolve before and after the lockdown (see Methods)[14]. This approach allows us to examine whether the parallel trend assumption is reasonable in the DiD models. Figure 3 plots our findings. In Fig. 3a, we compare the AQI between the treatment and control groups before and after lockdowns. We find that there is no systematic difference in the trends between the two groups before the city lockdown, that is, the estimated coefficients for the lead terms ($k \leq -2$) are all statistically insignificant. That implies the parallel trend assumption would be reasonable in the absence of the lockdown. In contrast, we see that the trends break after the city lockdown, that is, the lagged terms ($k \geq 0$) become negative and statistically significant. The AQI dropped by 20–30 points within two weeks after lockdown, and this result remains statistically significant in subsequent periods. The corresponding regression results are reported in Supplementary Table 5.

In Fig. 3b, we repeat this exercise to investigate the air quality trend in cities in the control group in 2019 and 2020. The results suggest that the air quality in 2019 could be a reasonable counterfactual for air quality in 2020 in the control group cities; we find that their trends in air quality before the beginning of the Chinese Spring Festival (25 January) in 2020 were also similar to those in 2019. The estimated coefficients after the festival show a slight reduction in air pollution, with the AQI reduced by 5 to 10 points. Supplementary Fig. 2 repeats the same exercise using log AQI, $PM_{2.5}$ and log $PM_{2.5}$ as the outcomes, and we observe very similar patterns. The corresponding regression results are reported in Supplementary Table 6.

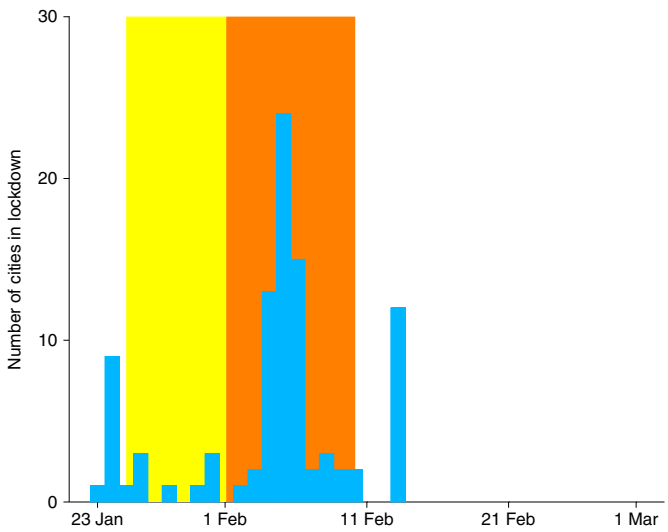

Fig. 2 | Timing of lockdowns. The numbers of cities in lockdown from 23 January to 1 March are shown, with yellow shading representing the Chinese Spring Festival holiday (25–30 January) and red shading showing the extended Spring Festival holiday (31 January to 10 February).

To validate the robustness of our results, we conducted some additional analyses. We investigated whether air quality levels between the treatment and control groups differ before and after the 2019 Spring Festival. If we find that air quality in the treatment group also improves after the holiday in a typical year, our findings may be driven by some unobserved differences between these two groups. The results show that the coefficient of the interaction term between the Spring Festival and the treatment group is statistically insignificant, suggesting that this is not likely to be the case (Supplementary Table 7). We also excluded cities in Hubei province, where COVID-19 was first detected in China (Supplementary Table 8a). All of the findings are similar, suggesting that our results are not driven by a few cities that were most affected by the virus. To deal with spillover concern, we also dropped the neighbouring cities of locked-down cities (Supplementary Table 8b). This is because the reduction in air pollution in locked-down cities could affect air pollution in neighbouring cities, which could lead to underestimation of the treatment effect. To deal with this issue, we cut such nearby cities from our analysis and compared the treatment cities with the control cities that were not affected by the policy change. We reached a similar conclusion, suggesting that the spillover effect is likely to be small.

As another way of checking the robustness of our findings, we used the sample before the Spring Festival to estimate the lockdown effect (Supplementary Table 9). Before the Spring Festival, only Wuhan and a few neighbouring cities enforced lockdown policies, and most other cities had not yet adopted any counter-virus measures. Using this restricted sample gives us a relatively 'clean' control group, but at the cost of a smaller sample size in the treatment group. We find that the results are again similar. We provide more discussion on these results in Supplementary Note 2.

Heterogeneity across cities. In Fig. 4, we investigate whether the effect of lockdown varies across different types of cities. Note that the heterogeneity analyses do not have causal interpretations but help us to understand the channels through which lockdowns affect air quality.

First, we compared colder cities with warmer cities and northern cities with southern cities. We expected the impacts of lockdown

Table 1 | The effects of lockdown on air quality

	Treatment and control group in 2020				Control group in 2019 and 2020			
	Levels		Log		Levels		Log	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(a) AQI								
Lockdown	−18.27***	−19.84***	−0.14***	−0.17***				
	(3.21)	(3.13)	(0.03)	(0.03)				
Spring Festival in 2020					−6.93***	−6.34***	−0.06***	−0.05**
					(2.14)	(2.13)	(0.02)	(0.02)
R^2	0.503	0.515	0.581	0.601	0.459	0.469	0.519	0.541
(b) $PM_{2.5}$ ($\mu g\,m^{-3}$)								
Lockdown	−12.87***	−14.07***	−0.13***	−0.17***				
	(2.60)	(2.53)	(0.03)	(0.03)				
Spring Festival in 2020					−7.64***	−7.05***	−0.09***	−0.07**
					(1.74)	(1.77)	(0.03)	(0.03)
R^2	0.534	0.541	0.627	0.641	0.472	0.479	0.553	0.570
Weather control		Y		Y		Y		Y
City fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Date fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects					Y	Y	Y	Y
Observations	19,764	19,764	19,764	19,764	27,938	27,938	27,938	27,938
Number of cities	324	324	324	324	229	229	229	229

Weather controls include daily temperature, its square, precipitation and snow depth. The fixed effects indicate a set of dummy variables (see Methods). Each column in each panel represents one separate regression. In the regressions indicated in columns (1), (3), (5) and (7), we do not control for the weather conditions; in other columns, we control for the weather conditions. In columns (1), (2), (5) and (6), the outcomes of interest are the absolute values of the pollutants. In columns (3), (4), (7) and (8), we take the logarithms on the pollutants as the outcomes. Standard errors are clustered at the city level and reported below the coefficients. **$P < 0.05$; ***$P < 0.01$.

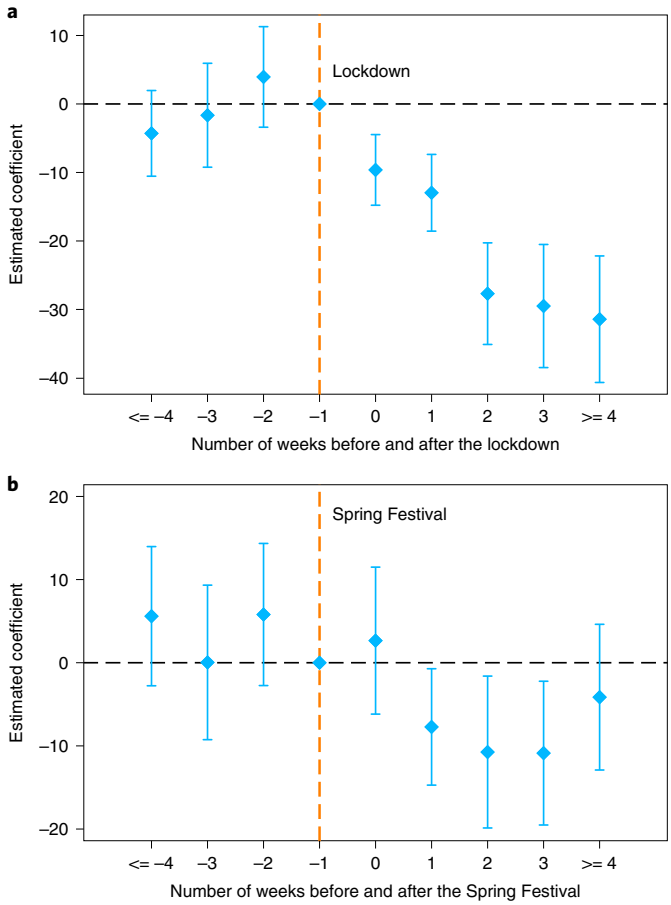

Fig. 3 | The effects of lockdown. a, The effects of lockdown on AQI. The air pollution levels between the treated cities are compared with the control cities, and the vertical line indicates the timing of lockdowns. **b**, The effects of general disease preventive measures on AQI in the control group (2019 and 2020). Air pollution levels in the control cities are compared between 2019 and 2020. The vertical line indicates the start of the Spring Festival holiday. We include leads and lags of the start of the city lockdown dummy in the regressions. In **a**, the dummy variable indicating one week before the lockdown is omitted from the regression; and in **b**, the dummy variable indicating one week before the 2020 Spring Festival is omitted from the regression. Thus, the difference in air quality one week before the treatment (lockdown in **a** or Spring Festival in **b**) is set to be zero and serves as the reference point (see Methods). Each estimate shows the difference in air quality relative to the difference one week before the lockdown (**a**) or 2020 Spring Festival (**b**). The estimated coefficients and their 95% confidence intervals (error bars) are plotted.

to be greater in colder and northern cities because these cities rely more heavily on inefficient and inflexible coal-based centralized winter heating systems in both residential and workplace buildings. The centralized winter heating systems were established in 1950s to 1980s following the model of the Soviet Union[15–17]: the government boils water in central facilities and delivers it to different buildings via networks of heating pipes. The hot water warms up the buildings and then flows back to the central facilities, where the water is boiled again. When the central heating system in a building is turned on, the entire building can be heated up. During the lockdown periods, people no longer need to work or go to school, so the heating in the office/school buildings can be entirely shut off, which will reduce coal consumption. In contrast, residential use of winter heating will not change much because residential buildings have to keep their winter heating systems on during the entire winter season. As a result, we expect the total demand for coal in northern Chinese cities to decrease after lockdowns, which will improve air quality. In comparison, southern Chinese cities are generally warmer and do not consume much coal in the workplace, so we expect the impact of city lockdown to be smaller. The top section of Fig. 4 confirms our conjecture: the impact of lockdown is larger in both colder and northern cities. The estimated reduction in the AQI is around 25–30 points for those cities and 5–10 points in warmer or southern cities.

In the middle section of Fig. 4, we examine the impact heterogeneity with respect to gross domestic product (GDP), GDP per capita and population. We find that the effect is greater in cities with higher GDP, higher income and larger population size. This is consistent with the fact that energy consumption is usually higher in more agglomerated economies, where more concentrated economic activities take place.

Finally, the bottom section of Fig. 4 shows that, in cities that rely more on industrial activities (measured by the manufacturing output, the number of firms, the volume of traffic and the emissions of different types of pollutant), the effect is more substantial.

This finding implies that coal consumption, industrial activity and transportation all contribute substantially to air pollution in China. We repeated our heterogeneity analysis for $PM_{2.5}$ and illustrate the results in Supplementary Fig. 3. Supplementary Table 10 presents the full set of results on AQI and $PM_{2.5}$.

Discussion

Our findings have important implications for several sets of policy-relevant questions. First, to understand the welfare implications of city lockdown, we need to quantify both the costs and benefits of the policy. Our result, that city lockdowns substantially improve air quality, is an essential component in assessing the benefits of such lockdowns. According to the World Health Organization, seven million deaths around the world can be attributed to air pollution each year, and the majority of them live in countries such as China and India, where air pollution levels are high[18].

In the Chinese context, a large number of studies have shown that air pollution adversely affects health outcomes, such as life expectancy[15,17], mortality[16,19,20] and morbidity[21–23]. It has also been found that air pollution affects mental health[24], cognition[25], productivity[26] and defensive expenditure[27]. Therefore, it is evident that air pollution has imposed a considerable burden, and the potential health benefits derived from the improvement in environmental quality following the COVID-19 pandemic could be substantial.

Second, while city lockdowns have substantially decreased air pollution levels, the high economic cost of doing so makes it a non-sustainable option for addressing the pollution issue. When compared with other environmental regulations implemented in China, we found that similar levels of air quality improvement can be achieved at a much lower cost. As summarized in Supplementary Table 11, for example, the restrictions on gasoline fuel standards alone could decrease AQI values by about 13% (ref. [28]), the Two Control Zone Policy (an emission regulation that targets high SO_2 regions) could reduce SO_2 by around 15–20% (refs. [29,30]) and the regulations during the Beijing Olympics were able to bring down PM_{10} concentrations by around 30% in the host cities[20,31]. In other words, it is highly inefficient to use city lockdowns to reduce pollution, and many other, cheaper, ways to achieve the same environmental target exist.

Third, the heterogeneity analysis shows that the effects of city lockdowns on air pollution are greater in cities with a larger economy, greater industrial activity and traffic volumes, and higher demand for coal heating. Not surprisingly, these results confirm that such activities are important sources of air pollution and highlight the necessity of controlling emissions from these sources when lockdown measures are eased.

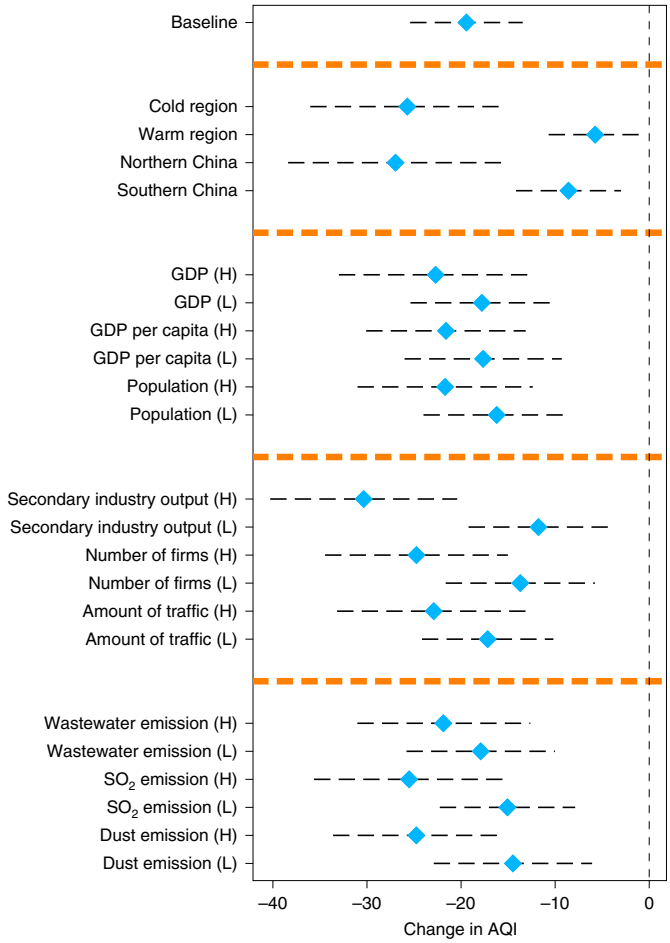

Fig. 4 | The heterogeneous effects of lockdowns on the AQI. Blue diamonds mark the estimated coefficients and the dashed black lines show 95% confidence intervals. Each row corresponds to a separate regression using a corresponding subsample. We use the mean values to separate the high (H) group from the low (L) group for each pair of heterogeneity analyses. For example, if a city's GDP is higher than the mean GDP, it falls into a high GDP group. For temperature (colder or warmer groups), we use data measured in the first week of our study period. North and South are divided by the Huai River. Other socio-economic data for the classification were measured in 2017. The dashed orange lines divide our heterogeneity analyses into four categories (from top to bottom): geographical and climatic conditions, socio-economic status, industrial activities, and emission level. Each regression implements the first model (equation (1)) and controls for the weather, city fixed effects, and date fixed effects.

Finally, the finding that the air pollution levels during the lockdown remained high is particularly alarming. The $PM_{2.5}$ concentration in locked-down cities was still more than four times higher than levels considered safe by the World Health Organization (WHO) ($10\,\mu g\,m^{-3}$ for the annual mean)[32]. This result suggests that other pollution sources continue to degrade local air quality during the lockdown period. As almost all non-essential production and business activities were suspended, residential consumption of energy becomes the last key emission source. In particular, in northern China, the government uses a coal-fired centralized system to provide winter heating to residents, and it has been found that this system can increase air pollution levels by 35–50% (refs. [15,16]). Our result implies that, without further reducing pollution from its reliance on coal for heating, it will be a real challenge for China to win its 'war on pollution'[33].

We conclude by pointing out three directions for future research. We only consider the short-term effects of city lockdowns, and it remains unknown whether the impacts are just a one-time shock or have changed people's behaviours permanently. If the shock is temporary, as people resume their normal activities, we would expect the improvement in air quality to be quickly offset in the longer term. Also, although improved air quality is beneficial to human health, the economic disruption caused by a lockdown can also have a negative impact on health outcomes. This points to the need to collect mortality and morbidity data to assess the overall health impact of this measure. Finally, if firm-level emission and output data become available in the future, the lockdown policy could be used to estimate the sector- and firm-specific abatement cost of pollution. Specifically, the emission data can tell us how much pollution abatement was achieved during the lockdown periods, while the production data can tell us how much output loss was associated with the pollution abatement. Combining these two, the cost of pollution abatement for different firms and industries can be determined. These analyses are beyond the scope of our paper, but future research on these issues is warranted to understand the full implications and draw valuable policy lessons from this unprecedented event.

Methods

Data. *Air quality data.* The air quality data comprises a high-frequency dataset covering seven major sets of air pollutants. We obtained these data from the Ministry of Ecology and Environment[34]. The original dataset includes hourly readings of the AQI, $PM_{2.5}$, PM_{10}, SO_2, O_3, NO_2 and CO concentrations from 1,605 air quality monitoring stations covering all of the prefectural cities in China. The AQI is a comprehensive measure of air pollution: the index is constructed using $PM_{2.5}$, PM_{10}, SO_2, CO, O_3 and NO_2 concentrations, with a lower AQI meaning better air quality. In China, the AQI is determined by the maximum concentration of different air pollutants. We summarize the relationship between the AQI and each pollutant in Supplementary Table 1.

To create the city-level air quality data, we first calculated the distance from a city's population centre to all monitoring stations within the corresponding city. We then aggregated station-level air pollution data to city-level data using the inverse distance weights. For this process, stations closer to the population centre are given higher weights so that city-level air pollution data can better represent the people dwelling in each city. The weights are inversely proportional to square distance.

Weather data. Weather data included temperature, precipitation and snow. These data were obtained from the Global Historical Climatology Network (GHCN) from the National Oceanic and Atmospheric Administration (NOAA)[35]. We collapsed these data to a daily city-level dataset using the same methods used for the air quality data.

Lockdown. We collected local governments' lockdown information city by city from the 'COVID-19 pandemic lockdown in Hubei' Wikipedia page[36] and various other news media and government announcements. Most of the cities' lockdown policies were directly issued by the city-level governments, although a few were promulgated by the provincial governments. To ensure compliance, civil servants and volunteers were assigned to communities, firms, business centres and traffic checkpoints. Local governments also penalized offenders if the rules were violated. There were some variations in rules and degree of the lockdown. For example, in some cities, individuals were not allowed to go out (food and daily necessities were delivered to them), while in other cities, they could go out if they did not have a fever. In this paper, we designated a city as locked down when the following three measures were all enforced: (1) prohibition of unnecessary commercial activities for people's daily lives, (2) prohibition of any type of gathering by residents, (3) restrictions on private (vehicles) and public transportation. Their geographical distributions and timings are presented in Figs. 1 and 2 and Supplementary Table 2.

Socio-economic status. To explore the heterogeneity, we assembled the cities' socio-economic status from the 2017 China City Statistical Yearbook[37]. It contains city-level statistics such as GDP, population, industrial output, number of firms, amount of traffic and pollutant emissions.

Summary statistics. We report the summary statistics of air pollution and weather variables during this period in Supplementary Table 3. The average AQI was 74, with a standard deviation of 42. The average $PM_{2.5}$ concentration was $52\,\mu g\,m^{-3}$, five times higher than the WHO standard ($10\,\mu g\,m^{-3}$ for annual mean, and $25\,\mu g\,m^{-3}$ for a daily mean). Cities that were locked down were, on average, more polluted than the control cities before the lockdowns. This is probably because Wuhan and its neighbouring cities are generally more polluted than cities that

are far away. We also saw a sharp decline in AQI and $PM_{2.5}$ concentrations after the lockdown.

Models. We used two sets of DiD models to identify the impact of counter-COVID-19 measures on air pollution. First, in our baseline regression, we estimated the relative change in air pollution levels between the treated and control cities using the following model:

$$Y_{it} = 1[\text{city lockdown}]_{it} \times \beta + \mathbf{X}_{it} \times \alpha + \mu_i + \pi_t + \varepsilon_{it} \quad (1)$$

where Y_{it} represents the level of air pollution in city i on date t. $1[\text{city lockdown}]_{it}$ denotes whether a lockdown is enforced in city i on date t, and takes the value 1 if the city is locked down and 0 otherwise. $\mathbf{X}_{it}$ are the control variables, including temperature, temperature squared, precipitation and snow depth. μ_i indicate city fixed effects and π_t indicate date fixed effects.

The city fixed effects, μ_i, which are a set of city-specific dummy variables, can control for time-invariant confounders specific to each city. For example, the city's geographical conditions, short-term industrial and economic structure, income and natural endowment can be controlled by introducing the city fixed effects. The date fixed effects, π_t, are a set of dummy variables that account for shocks that are common to all cities in a given day, such as the nationwide holiday policies, macroeconomic conditions and the national air pollution trend over time.

As both location and time fixed effects are included in the regression, the coefficient β estimates the difference in air pollution between the treatment (locked down) cities and the control cities before and after the enforcement of the lockdown policy. We expected β to be negative, as industrial and business activities were restricted in the locked-down cities, and thus their air pollution levels should greatly decrease.

Because some of the treated cities and the control cities are closely located, the reduction in the air quality in the treatment cities could affect air quality in other cities, creating a potential spillover effect. In our research setting, accounting for this spillover effect is challenging because the spillover not only depends on the timings of lockdown policies and the geographical distribution of treatment and control cities, but also depends on wind directions in different cities. So, strictly speaking, β measures the relative effect of the city lockdown on air pollution between the two groups of cities, rather than the absolute impact. In an attempt to test for the size of the spillover effect, we compared the treatment cities with a set of 'clean' control cities, which are those cities (1) without lockdown policies and (2) not neighbouring any lockdown cities. The underlying assumption of this test is that cities neighbouring the lockdown cities are most likely to be affected by the spillover effect (so they should be excluded from the analysis). As reported in Supplementary Table 8b, we obtained quantitatively similar results using this subsample. We thus concluded that the spillover effect does not bias our estimates in any substantial way.

The underlying assumption for the DiD estimator is that lockdown and control cities would have parallel trends in air quality in the absence of the event. Even if the results show that air quality improves in the locked-down city after its enforcement, the results may not be driven by the lockdown policy, but by systematic differences in treatment and control cities. For example, if treatment cities have an improving trend in air quality, this could drive the results. This assumption is untestable because we cannot observe the counterfactual: what would happen to the air pollution levels in the locked-down cities if such policies were not enforced. Nevertheless, we can still examine the trends in air quality for both groups before lockdown implementation and investigate whether the two groups are indeed comparable. To do so, we conducted the event study and fitted the following equation[12]:

$$Y_{it} = \sum_{m=k, m\neq -1}^{M} 1[\text{city lockdown}]_{it,k} \times \beta^k + \mathbf{X}_{it} \times \alpha + \mu_i + \pi_t + \varepsilon_{it} \quad (2)$$

where $1[\text{city lockdown}]_{it,k}$ are a set of dummy variables indicating the treatment status at different periods. Here, we put 7 days (one week) into one bin (bin $m \in M$), so that the trend test is not affected by the high volatility of the daily air pollution. The dummy for $m = -1$ is omitted in equation (2) so that the post-lockdown effects are relative to the period immediately before the launch of the policy. The parameter of interest β^k estimates the effect of city lockdown m weeks after the implementation. We included leads of the treatment dummy in the equation, testing whether the treatment affects the air pollution levels before the launch of the policy. Intuitively, the coefficient β^k measures the difference in air quality between cities under lockdown and otherwise in period k relative to the difference one week before the lockdown. We expected that lockdown would improve air quality with β^k being negative when $k \geq 0$. If the pre-treatment trends are parallel, β^k would be close to zero when $k \leq -2$.

Even in a city that did not have a formal lockdown policy, people's daily lives could still have been affected by the counter-virus measures. In fact, in all Chinese cities, the Spring Festival holiday was extended, and people were advised to stay at home when possible, enforce social distancing and maintain good hygiene. We examined this possibility by comparing the air pollution changes between 2019 and 2020 for the same period within the control group. As the explosion of the COVID-19 cases coincided with China's Spring Festival (SF), we investigated whether the trend of air quality in 2020 differed from the trend in 2019 after the festival, by fitting the following model:

$$Y_{itj} = 1[\text{SF} \times 1(\text{year} \geq 2020)]_{itj} \times \beta + \mathbf{X}_{itj} \times \boldsymbol{\alpha} + \mu_i + \pi_t + \gamma_j + \varepsilon_{itj} \quad (3)$$

where j represents year. $1[\text{SF} \times 1(\text{year} \geq 2020)]_{itj}$ is our variable of interest, and it takes the value 1 if it is after the start of the Chinese Spring Festival in the year 2020, and 0 otherwise. Because the national government announced that "the virus can transmit from people to people" on the 20 January, and the extension of the national holiday was announced on the 26 January, we think that the normal cities were affected by the virus and launched the containment actions from the beginning of the national holiday. The value of β would be 0 if the coronavirus and countermeasures do not affect control cities.

The identifying assumption for equation (3) is similar to equation (1). For the parallel trend assumption to be reasonable, the trends in air quality before the Spring Festival in 2019 are required to be similar to the trends in air quality in the corresponding period in 2020. We can investigate patterns in air pollution around the holiday analogously using equation (2). In all the regressions, we clustered the standard errors at the city level.

Combining the results from the two DiD models, we were able to evaluate the overall impact of city lockdowns. Our first DiD measures how the city lockdown improves air quality relative to non-locked down cities in 2020 (equation (1)), and the second DiD assesses how national-level disease preventive measures (for example, all cities extended the Spring Festival holiday, required social distancing and urged people to stay at home) affect non-locked-down cities relative to the same season in previous years (equation (3)). Therefore, summing up the two DiD estimates (equation (1) and equation (3)), we could infer the overall impacts of city lockdowns on air quality.

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

All data necessary for replication will be available at the public repository (https://github.com/yhyhpan/COVID19_LOCKDOWN) to reproduce the results presented in this paper upon publication.

Code availability

All code necessary for replication will be available at the public repository (https://github.com/yhyhpan/COVID19_LOCKDOWN) to reproduce the results presented in this paper upon publication.

Received: 6 April 2020; Accepted: 18 June 2020;
Published online: 7 July 2020

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Acknowledgements

We thank A. Park, K. Kawaguchi, R. Kaiji Gong, J. Li, Y. Lin, T. Liu, Q. Wang, H. Zhang, S. Zhang and seminar participants at HKUST and Global Open Series in Environmental Economics (GoSee) for their insightful comments. T.T. also thanks the Bai Xian Asia Institute for support as a Bai Xian Scholar.

Author contributions

All authors equally contributed to the paper. G.H., P.Y. and T.T. conceptualized the study and carried out initial planning. P.Y. retrieved and constructed the dataset. P.Y. carried out the statistical analysis, which was refined by T.T. and G.H. for the final version. T.T. prepared the first draft of the manuscript, which was revised by P.Y. and G.H. All authors reviewed and contributed to a final draft and approved the final version for publication.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information is available for this paper at https://doi.org/10.1038/s41893-020-0581-y.

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Last updated by author(s): Apr 9, 2020

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Research sample	The data covers 324 cities in China.
Sampling strategy	We do not employ any sampling strategy. As described in the data section, we use all publicly available air quality data from 1,605 monitoring station, and weather data from data on air quality, weather, city lockdown, and city information.
Data collection	This paper uses publicly available dataset. Air quality data were collected from the Ministry of Ecology and Environment of China. The weather data were collected from Global Histroical Climatology Network from the National Oceanic and Atmospheric Administration in the U.S. The lockdown data were collected from multiple sources including news media and government disclosures. The city level socioeconomic data were collected from 2017 China City Statistical Yearbook.
Timing	The sample period is from January 1st to March 1st in 2020. Part of the analysis also uses data in the same season in 2019.
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