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Non-negligible contributions to human health from increased household air pollution exposure during the COVID-19 lockdown in China

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ABSTRACT

Background: Ambient and household air pollution are found to lead to premature deaths from all-cause or cause-specific death. The national lockdown measures in China during COVID-19 were found to lead to abrupt changes in ambient surface air quality, but indoor air quality changes were neglected. In this study, we aim to investigate the impacts of lockdown measures on both ambient and household air pollution as well as the short-term health effects of air pollution changes.

Methods: In this study, an up-to-date emission inventory from January to March 2020 in China was developed based on air quality observations in combination with emission-concentration response functions derived from chemical transport modeling. These emission inventories, together with the emissions data from 2017 to 2019, were fed into the state-of-the-art regional chemistry transport model to simulate the air quality in the North China Plain. A hypothetical scenario assuming no lockdown effects in 2020 was also performed to determine the effects of the lockdown on air quality in 2020. A difference-to-difference approach was adopted to isolate the effects on air quality due to meteorological conditions and long-term decreasing emission trends by comparing the PM 2.5 changes during lockdown to those before lockdown in 2020 and in previous years (2017–2019). The short-term premature mortality changes from both ambient and household PM 2.5 changes were quantified based on two recent epidemiological studies, with uncertainty of urban and rural population migration considerations.

Findings: The national lockdown measures during COVID-19 led to a reduction of 5.1 µg m⁻³ in ambient PM 2.5 across the North China Plain (NCP) from January 25th to March 5th compared with the hypothetical simulation with no lockdown measures. However, a difference-to-difference method showed that the daily domain average PM 2.5 in the NCP decreased by 9.7 µg m⁻³ between lockdown periods before lockdown in 2020, while it decreased by 7.9 µg m⁻³ during the same periods for the previous three-year average from 2017 to 2019, demonstrating that lockdown measures may only have caused a 1.8 µg m⁻³ decrease in the NCP. We then found that the integrated population-weighted PM 2.5 exposure, increased by 5.1 µg m⁻³ during the lockdown periods compared to the hypothetical scenario, leading to additional premature deaths of 609 (95% CI: 415–775) to 2,860 (95% CI: 1,436–4,273) in the short term, depending on the relative risk chosen from the epidemiological studies.

Interpretation: Our study indicates that lockdown measures in China led to abrupt reductions in ambient PM 2.5 concentration but also led to significant increases in indoor PM 2.5 exposure due to confined indoor activities and increased usages of household fuel for cooking and heating. We estimated that hundreds of premature deaths were added as a combination of decreased ambient PM 2.5 and increased household PM 2.5. Our findings suggest...
that the reduction in ambient PM$_{2.5}$ was negated by increased exposure to household air pollution, resulting in an overall increase in integrated population weighted exposure. Although lockdown measures were instrumental in reducing the exposure to pollution concentration in cities, rural areas bore the brunt, mainly due to the use of dirty solid fuels, increased population density due to the large-scale migration of people from urban to rural areas during the Chinese New Year and long exposure time to HAP due to restrictions in outdoor movement.

1. Introduction

To prevent the spread of COVID-19, which was first officially reported in late December 2019 in Wuhan, China, the Chinese government adopted emergency orders to lock down Wuhan from January 23rd to April 8th. Shortly after the lockdowns in Wuhan, many areas in China experienced “closed management” or “restricted outdoor activity” on a community basis depending on the region, in which nonessential businesses and factories were closed and intercity travel was restricted (https://en.wikipedia.org/wiki/COVID-19_pandemic_lockdown_in_Hubei, last accessed July 7th, 2020). Undoubtedly, the stringent lockdown measures in China were successful in controlling the spread of the virus (Tian et al., 2020) and provided a natural experiment to study how human activity could affect local and regional air pollution. The implementation of stringent lockdown resulted in less travel, traffic and industrial emissions. A significant drop in nitrogen dioxides (NO$_2$) was detected by satellite remote sensing data (Marlier et al., 2020; Bauwens et al., 2020; Liu et al., 2020a; Miyazaki et al., 2020; Le et al., 2020) as well as ground surface observations (Bao et al., 2020; Huang et al., 2020; Shi and Brasseur, 2020; He et al., 2020). However, other air pollutants, such as particulate matter with diameters less than 2.5 µm (PM$_{2.5}$) and ozone, exhibited different patterns due to the complex nonlinear response of these pollutants to meteorological conditions (Wang et al., 2020; Le et al., 2020; Liu et al., 2020b).

Exposure to ambient air pollution (AAP), such as PM$_{2.5}$ and ozone, could have chronic and acute side effects on human health, increasing hospital and emergency room admissions and premature deaths (Kloog et al., 2013; Fann et al., 2018; Burnett et al., 2014, 2018; Turner et al., 2016). Long-term exposure to air pollution, including ambient and household exposure, contributed to 6.67 million deaths from ischemic heart disease, lung cancer, chronic obstructive pulmonary disease (COPD), lower respiratory infections (such as pneumonia), stroke, type 2 diabetes and adverse birth outcomes worldwide in 2019 according to the new State of Global Air 2020 study (SOGA2020). The SOGA2020 report also highlighted that, globally, nearly 500,000 infants died in their first month of life in 2019 from health effects associated with air pollution exposure, with nearly two-thirds (64%) related to household air pollution (HAP). The SOGA2020 also estimated that 3.8 billion people (47% of the global population) were exposed to HAP, and 2.31 million premature deaths were due to exposure to HAP in 2019 (approximately 4% of all global deaths). The societal lockdown for COVID-19 was first implemented in Wuhan, China, on January 23, 2020, and then implemented domestically in mainland China after the end of the Spring Festival period (“Chunyun”, early February in 2020, Liu et al., 2020a; Liu et al., 2020b). Chunyun is usually a period of 40 days—15 days before and 25 days after the Chinese New Year (CNY)—during which there are high rates of travel for migrant workers moving from urban areas to rural areas to reunite with their families. During the lockdowns, more people were exposed to the increased usages of household solid fuels for cooking and heating, as they were trapped in their rural areas due to the lockdowns (Fan et al., 2020). With people confined to their homes during the lockdown, the exposure time to polluting household air also increased. An average person would usually spend approximately 20% of their day outside the house, where air pollution was 3–20 times less than that found indoors with solid fuel use. These dynamics have changed markedly in the recent months. Meanwhile, the shift to indoor food cooking also posed a greater health risk for all family members, including the elderly, children and the already affected females. One recent study showed that total population-weighted PM$_{2.5}$ actually increased by 5.7 µg m$^{-3}$ during the 2020 COVID-19 lockdown in China when both ambient and indoor air pollution exposure were considered but decreased by 16.7 µg m$^{-3}$ if only ambient air pollution was considered (Shen et al., 2021), highlighting the significance of increased indoor air pollution in quantifying health exposures.

Several studies have discussed the short-term health impacts of air quality improvement due to abrupt lockdowns. One recent study estimated the associated short-term health effects from air pollution reductions (NO$_2$ and PM$_{2.5}$) during COVID-19 in China and concluded that improved air quality could avert a total of 8,911 (95% CI: 6,950–10,866) deaths associated with NO$_2$ and 3,214 (95% CI: 2,340–4,087) deaths related to PM$_{2.5}$ due to air quality improvement from January 1, 2020 to March 14, 2020 (Chen et al., 2020a; Chen et al., 2020b; Giani et al., 2020). However, these two studies fail to consider indoor air pollution and its associated health effects. Several studies have emphasized the possible deterioration of indoor air pollution resulting from home isolation due to COVID-19 (Aboueleish, 2020; Du and Wang, 2020; Du et al., 2021a; Du et al., 2021b; Ezani et al., 2021; Thakur et al., 2020; Shen et al., 2021). In this study, we innovatively assessed both ambient and indoor PM$_{2.5}$ changes due to lockdowns and evaluated the short-term health impacts of PM$_{2.5}$ changes by using up-to-date emission data from 2020, a state-of-the-art regional chemical transport model (CTM), an integrated exposure assessment model and the latest epidemiological studies.

2. Methods

2.1. Model evaluation after adjusting the emissions

In this study, to reduce uncertainty from the CTM we applied the assimilated emission inventory developed by Xing et al. (2020) for real-time simulations. The emissions of NO$_2$, SO$_2$, volatile organic compounds (VOCs) and primary PM$_{2.5}$ in the North China Plain (NCP) decreased by 51%, 28%, 67% and 63% due to the COVID-19 lockdown. Compared with the hypothetical scenario, assuming no COVID-19 lockdown, NME (normalized mean error) for PM$_{2.5}$ and O$_3$ decreased by 0.17 and 0.13, respectively, in February (Table S2). In addition, the deficiency of chemical mechanisms in the CTM (e.g., conversion of SO$_2$ to SO$_3$) is another source of uncertainty. In this study, we used the latest version CMAQ (community multiscale air quality model, v5.3.1, see Section 2.2) to reduce this uncertainty (Appel et al., 2020). The model statistics shown in Table S2 (R, NMB, NME) are comparable to previous studies (Hu et al., 2016; Chang et al., 2018; Guo et al., 2019). Therefore, the results from our CTM are reliable for follow-up health assessment. With the updated emissions (Xing et al., 2020), the model will predicated PM$_{2.5}$ in the NCP before and after lockdown, with NMB (normalized mean bias) ranging from 0.10 before to 0.04 after lockdown. The model also shows underestimation of PM$_{2.5}$ during lockdown periods for the entire NCP, with NMB ranging from −0.11 in Hebei to −0.35 in Shandong provinces, with a domain average of −0.25 for the NCP (Fig. 1; Table S2). We also included the model evaluation for the emissions without considering the COVID-19 lockdown, which significantly underestimates ozone and overestimates PM$_{2.5}$ from January 23rd to March 5th (Fig. 1b). With comparison to the no-shutdown effect (Fig. 1b,d), our model performed much better in...
capturing the day-to-day variations for both ozone and PM$_{2.5}$ during lockdown periods, with R (correlation coefficient) values all above 0.63 for O$_3$ before, during and after lockdowns and above 0.76 for simulated PM$_{2.5}$ during the same period (Table S2).

### 2.2. Air quality model configuration and simulations

The air quality changes were simulated using the coupled WRF (weather research and forecasting model, v.3.9.1-CMAQ (v5.3.1, https://doi.org/10.5281/zenodo.3585898) model. The coupled model was set up using nested simulations with the first layer covering East Asia with a horizontal resolution of 27 km × 27 km and the second layer covering the North China Plain with a horizontal resolution of 9 km × 9 km (Fig. S1 in the Supporting Information). The physical parameters for the WRF model are listed in Table S1. The meteorological field data from the WRF model were then processed through a meteorology chemistry interface processor (MCIP) to transform the data into the format that CMAQ can read. Carbon bond 6 (CB6) and AER07 used in CMAQ model.

To eliminate the influence of the initial conditions, the simulation was carried out for five days in advance from the first day of the simulation period. The simulation period was January 2020 to March 2020. We ran two sensitivity simulations: one using the updated real-time emissions in 2020 derived from our response model (Xing et al., 2020) and the other scenario considering the consistent emissions from January 1 to March 31 in 2020 without the effects of COVID-19. We also ran 3-month simulations from January to March from 2017 to 2019. For the emission inventory for these three years, we used the bottom-up method (Ding et al., 2019), without considering the emission changes caused by the “Chunyun” effect from the Chinese Spring Festival, which usually starts in late January and early February each year. For ambient air pollution, we focused on surface ozone and PM$_{2.5}$ only. The updated real-time emissions in 2020 derived from our response model will also likely capture the emission changes caused by restricted fireworks, as discussed by Brimblecombe and Lai (2020).

### 2.3. Integrated assessment of ambient and household air pollution

To comprehensively evaluate the health impact of both AAP and HAP PM$_{2.5}$ exposure, we took advantage of the integrated population-weighted exposure to PM$_{2.5}$ (IPWE), defined as the weighted sum of PM$_{2.5}$ concentrations in all microenvironments where people spend time, including the living room, bedroom, kitchen and outdoor environment (Aunan et al., 2018; Zhao et al., 2018). The IPWE was calculated in the following equation:

\[
\text{IPWE} = \text{PWE}_{\text{AAP}} + \text{PWE}_\text{HAP}
\]  

where PWE$_{\text{AAP}}$ denotes the population-weighted exposure of AAP, and PWE$_{\text{HAP}}$ refers to the population-weighted exposure of HAP. The PWE$_{\text{AAP}}$ was calculated by averaging the weighted geographic ambient PM$_{2.5}$ concentration by the total population. The PWE$_{\text{HAP}}$ was calculated using the following equation:

\[
PWE_{HAP} = \frac{1}{P} \sum_{i,j,k} (P_{ij,k} \times HAP_{ij,k})
\]  

where P is the population in the geographic unit and HAP$_{ij,k}$ is the extra PM$_{2.5}$ exposure level of solid fuel users at geographic unit (i) for different societal settings (j, urban or rural) using various household cooking fuel types (k, i.e., coal and biomass). The definitions of urban and rural populations follow the definitions in China’s official statistics. The geographic unit (i) used in our calculation is the intersection of counties and a 9 km × 9 km model grid such that the data sources with the highest resolution are utilized. While indoor PM$_{2.5}$ may arise from a wide range of sources, the PM$_{2.5}$ from solid fuel combustion has received the most attention around the world. Some internationally renowned organizations or research programs, such as the World Health Organization and the Global Burden of Disease (GBD) study, regard solid fuel combustion as the only leading source of indoor PM$_{2.5}$ and use “HAP” to refer to the pollution caused by household solid fuel combustion. NCP is a region where rural people burn a large amount of solid fuels for cooking and heating (Zhao et al., 2018; Liu et al., 2016; Yun et al., 2020; Shen et al., 2021), therefore we consider solid fuels to be a leading source of indoor PM$_{2.5}$ in this region. Smoking may be another noticeable source of indoor PM$_{2.5}$, but it is not likely to be affected significantly by population migration and is thus not considered in this work.

We adopt the HAP$_{ij,k}$ values derived in our previous studies (Aunan et al., 2018; Zhao et al., 2018). It is noted, however, that we only used the wintertime HAP$_{ij,k}$ since our time period of interest is mostly in winter. The average wintertime HAP$_{ij,k}$ for urban and rural biomass users were estimated to be 276 (95% confidence interval (CI): 155–397) µg m$^{-3}$ and 309 (95% CI: 223–396) µg m$^{-3}$, respectively, and the corresponding values for urban and rural coal users were 47 (95% CI: 35–59) µg m$^{-3}$ and 145 (95% CI: 121–168) µg m$^{-3}$, respectively. No extra HAP exposure was considered for clean fuel users. FY$_{ij,k}$ were derived in our previous study (Zhao et al., 2018) for 2005–2015 and updated to our time period of interest using the same method.

### 2.4. Population migration and changes in time-activity patterns

A large number of migrant workers move from the regions where they work to their hometowns (normally from urban to rural areas) to reunite with their families before the Spring Festival and usually return to work shortly after the Spring Festival. In 2020, return-to-work migration was frozen to some extent by the COVID-19 lockdowns. The population migration associated with the Spring Festival and COVID-19,
changed the population in various administrative regions and society settings (i.e., \( P_{ij,k} \) in Eq. 2), thereby altering HAP exposure and IPWE. Here, we obtain the daily number of migrants by combining the total number of migrants reported by the 6th National Population Census in 2010 and the time series of migration intensity from the “Baidu Migration” platform. The 6th National Population Census provides detailed sources, destinations, and numbers of migrants at the county level. The migration between a pair of sources and destinations is classified into four types: urban-to-urban, urban-to-rural, rural-to-urban, and rural-to-rural. Using these data, and assuming that 90% of migrants return home to celebrate the Spring Festival, we derive the number of urban and rural people moving in and out of each province before the 2020 Spring Festival. The Wuhan lockdown began on January 23, two days before the Spring Festival (January 25). On January 24 and 25, some provinces activated the “first-level public health emergency response”, but the restrictions were mostly limited to transportation from and to Hubei Province (where Wuhan is located). Based on the “Baidu Migration” data used in this work (https://baike.baidu.com/item/2020%E5%B9%B4%E6%98%A5%E8%8B%B0/241439997?fr=aladdin), the populations migrating into and out of the five provinces of interest during January 23–25, 2020 were 8.8% and 2.5% larger than the migrating populations during the same period of 2019 (based on the Chinese lunar calendar). The corresponding inflow and outflow populations during the previous 10 days (i.e., January 13–22, 2020) were 6.8% and 5.9% larger than the migrating populations during the same period of 2019. This confirms that the population migration before the Spring Festival in the five provinces was not significantly affected by COVID-19. Therefore, we assumed that the same fraction of the population returned home to celebrate the Spring Festival in 2020 as in 2010. We subsequently allocate the number of migrants to each individual day between January 1 and January 25 (i.e., the Spring Festival) using the cross-province migration intensity reported by the “Baidu Migration” platform as a surrogate. For return-to-home migration, we use the cross-province migration intensities during January 26 to March 31, 2020, and the same period in 2019 (based on the lunar calendar) to estimate the fraction of migration that was completed by March 31. We estimate that 69% of migrants had returned to work by March 31, ranging from 42% in Beijing to 86% in Shanxi. The number of return-to-work migrants was then allocated to each day following the method described above. To account for the uncertainty in population migration, we assume that the number of migrants follows a uniform distribution with a variation interval of ± 30%.

In addition to changing population migration, lockdown measures forced people to spend a longer time indoors, which also affected IPWE variation interval of above. To account for the uncertainty in population migration, we allocated grants was then allocated to each day following the method described

42% in Beijing to 86% in Shanxi. The number of return-to-work migrants was then allocated to each day following the method described above. To account for the uncertainty in population migration, we assume that the number of migrants follows a uniform distribution with a variation interval of ± 30%.

The Chinese Research Academy of Environmental Sciences conducted a survey of household coal use for the period before and during the lockdown, which can be used to cross check our estimates of the changes in time-activity patterns and the populations using solid fuels. The household coal survey shows that household coal consumption in the NCP increased by 41% from pre lockdown to lockdown. Our calculation indicates that the coal-using population increased by 9% based on the estimated population migration and the fraction of coal-using populations in each geographic unit and societal setting. In addition, the time spent indoors per day was found to have increased from 19.0 h to 23.2 h in rural areas. Assuming that household fuels are not used during the time away from home and for 5 h at night, the above increase in indoor time would translate into a 30% increase in coal-use time, which we assumed to be a 30% increase in coal use per capita. Combined with the 9% increase in the coal-using population, we estimate a 42% increase in coal consumption from pre lockdown to lockdown, which is similar to the estimate from the survey data (41%). This consistency strengthens the robustness of our estimate of the HAP exposure change during the lockdown.

2.5. Short-term and long-term health impact assessment

Prevented short-term premature deaths during the lockdown period were calculated for each day using the following equation:

\[
\Delta \text{Mort} = \text{Pop} \times Y_0 \times AF
\]  

where \( \Delta \text{Mort} \) refers to daily prevented premature deaths due to PM\(_{2.5}\) changes in 2020 compared with previous years, \( \text{Pop} \) is the domain average population, and \( AF \) is the attributable fraction. \( AF \) is calculated as \((1–1/RR)\), with \( RR \) referring to the relative risk of death from all-cause and a specific disease. The \( RR \) is calculated using Equation 2:

\[
RR = e^{\beta \Delta x}
\]

where \( \beta \) refers to the cause-specific coefficient derived from epidemiology studies, and \( \Delta x \) is the daily PM\(_{2.5}\) concentration in 2020 compared with previous years. We adopted two \( \beta \) values from recent studies to discuss the uncertainties related to the short-term health impact assessment (Table S5). One study is from Atkinson et al. (2014), who performed a comprehensive systematic review and meta-analysis of 110 peer-reviewed time-series studies, reporting a 1.04% (95% CI: 0.52% to 1.56%) increase in the all-cause mortality associated with a 10 \( \mu \text{g} \text{m}^{-3} \) daily PM\(_{2.5}\) increase. Atkinson et al. (2014) also reported a significant association for respiratory causes of death of 1.51% (95% CI: 1.01% to 2.01%) and cardiovascular causes of 0.84% (95% CI: 0.41% to 1.28%) associated with a per 10 \( \mu \text{g} \text{m}^{-3} \) daily PM\(_{2.5}\) increase. The other study was a nationwide time-series analysis in 272 representative Chinese cities from 2013 to 2015, which reported a 0.22% (95% CI: 0.15%–0.28%) increase from total nonaccidental causes, 0.27% (95% CI: 0.18%–0.36%) from cardiovascular diseases and 0.29% (95% CI: 0.17%–0.42%) from respiratory diseases with each 10 \( \mu \text{g} \text{m}^{-3} \) increase in 2-day running average of PM\(_{2.5}\) concentrations (Chen et al., 2017).

For the short-term health assessment, we used national average baseline mortality rates for all-cause cardiovascular and respiratory diseases from the Global Burden of Diseases, Injuries, and Risk Factors Study 2017 (GBD 2017) (Stanaway et al., 2018), as suggested in previous studies (Dominici et al., 2006; Chen et al., 2017). In this study, we mainly discuss the results adopting the RR from the Chinese epidemiological study by Chen et al. (2017) and use the other RR by Atkinson et al. (2014) for comparison. Uncertainty analysis for the health results was calculated by running 50,000 Monte Carlo simulations, including the uncertainty ranges from population migration, outdoor activity time duration, extra PM\(_{2.5}\) exposure levels of solid fuel users, and the RR.
3. Results

3.1. Updated emission inventory during lockdowns in 2020

The up-to-date emission inventory during the lockdowns from January to March 2020 is described in our recent publication (Xing et al., 2020), and we will briefly discuss it here. Traditional anthropogenic emission inventories usually lag because of time-consuming efforts required to obtain the latest emission activity data (Zheng et al., 2018). Here, we developed a novel method to estimate real-time emission changes based on air quality observations in combination with emission-concentration response functions derived from chemical transport modeling (Xing et al., 2020). The principle of this novel model (hereafter “the response model”) is to match the concentration predicted by the model with surface observations by adjusting the assumed prior emissions. The anthropogenic emissions of NOx, SO2, VOC and primary PM2.5 were reduced by 51%, 28%, 67% and 63% due to the COVID-19 shutdown on the North China Plain. The main emission sectors all contribute to this emissions decrease. Significant data on traffic flow indicate that vehicle emissions decreased up to 55% in Beijing during the lockdown (Wang et al., 2020). Similarly, emissions from domestic fuel combustion, industry engineers and power plants decreased by more than 50%, 70% and 25% throughout China (Wu et al., 2020). In general, the performance for simulating the surface PM2.5 and ozone in 2020 was greatly improved by using the adjusted emission inventories from our response model (see Fig. 1 below and Fig. 4 in Xing et al., 2020).

3.2. Ambient air pollution exposure changes due to the lockdown

Previous studies have shown significant drops in ambient PM2.5 concentrations (AAP_PM2.5) as well as other pollutants (NOx), during the lockdowns in China (Shi & Brasseur, 2020; Liu et al., 2020a; Liu et al., 2020b; Miyazaki et al., 2020; Nie et al., 2020; Pei et al., 2020; He et al., 2020), despite spikes in several extreme haze events (Wang P. et al., 2020; Huang et al., 2020; Le et al., 2020). The PM2.5 drops observed from surface observations are well captured by our model and simulated using the updated emissions (Fig. 1b; Fig. S2). We compare the AAP_PM2.5 changes between the scenario considering the emission reductions during the COVID-19 lockdown with the hypothetical scenario without COVID-19-related emission drops. As shown in Fig. 2, compared with the hypothetical scenario, there were significant drops in AAP_PM2.5 concentrations, with higher than 50 μg m$^{-3}$ at some locations in Shandong and Henan provinces (Fig. 3b), with a domain average of 5.1 μg m$^{-3}$ decreases over the entire NCP during the entire lockdown period. The PM2.5 decreases were dominated by the changes in organic matter, unspeciated compositions and sulfate (Figs. S2 & S3). However, we note that these differences are a combination of emission changes caused by both national lockdown measures and the Chinese Spring Festival, since we are unable to tease out the emission changes caused by the annual Chinese Spring Festival effect (see Methods Section 2.2).

Hence, we then suggest using a difference-to-difference approach to compare the PM2.5 changes before and during the lockdown in 2020, as well as the PM2.5 changes during the same periods from 2017 to 2019 as simulated by the same model (see Methods). The emission inventories for 2017 to 2019 were processed in the same way as 2020, and the Chinese Spring Festival effects were not considered. By using this difference-to-difference approach, we could control the long-term air pollution decreasing trend caused mainly by the emission changes as well as the meteorological differences in 2020 with previous years (Chen et al., 2020a; Chen et al., 2020b). We determined that in 2020, the daily domain average AAP_PM2.5 in the NCP decreased by 9.7 μg m$^{-3}$ between the lockdown period and before lockdown in 2020 (Fig. S2a), while it decreased by 7.9 μg m$^{-3}$ during the same period for the previous three-year average from 2017 to 2019 (Table S3). We estimate that the lockdown measures in 2020 may have only caused a 1.8 μg m$^{-3}$ decrease in the NCP domain during the lockdown. To confirm our model findings, we also estimated the PM2.5 changes caused by the lockdown in 2020 by applying the same difference-to-difference approach to both the 233 surface observations and model outputs from 2017 to 2020 (Table S4). We determined that in 2020, the daily domain average AAP_PM2.5 in the NCP decreased by 30.2 μg m$^{-3}$ between the periods before and after the lockdown in 2020 (Fig. S3a), while it decreased by 24.4 μg m$^{-3}$ during the same periods for the previous three-year average from 2017 to 2019, leading to a 5.9 μg m$^{-3}$ decrease caused solely by the lockdown measures.

For these observation sites simulated by the model, we estimate that NCP decreased by 40.1 μg m$^{-3}$ between the period before and after the lockdown in 2020 (Fig. S3a), while it decreased by 27.2 μg m$^{-3}$ during the same period for the previous three-year-average from 2017 to 2019, leading to a 12.9 μg m$^{-3}$ decrease caused solely by the lockdown measures. Both observational and model results show that the PM2.5 decreases caused by the lockdown may be lower than the meteorological and interseasonal variations. This conclusion is consistent with a recent finding that the COVID-19 lockdown measures abruptly caused a smaller than expected influence on surface air quality after the changes were adjusted for trends in weather (Shi et al., 2021). Due to limitations of emission inventories, as well as chemical and physical parameters, our model estimated changes that were lower than the surface observations. We concluded that from the point view of AAP, the lockdown measures bring benefits on reducing ambient PM2.5, with comparison to both no-
lockdown measures and historical periods but may not as significantly as previous studies have reported.

3.3. Household air pollution exposure changes due to the lockdown

During the national lockdown in China, exposure to HAP may have been enhanced because people spent more time indoors and because many people were confined to their rural hometowns, resulting in more solid fuel use. In Fig. 3, we present the integrated population-weighted PM$_{2.5}$ exposure (IPWE) changes in the NCP, including both ambient (PWE$_{AAP}$) and indoor exposure (PWE$_{HAP}$). During the lockdown periods, the daily average PWE$_{AAP}$ in the NCP was 13.0 µg m$^{-3}$ lower compared with the hypothetical simulation, where the lockdown wasn’t considered as a combination of effects from COVID-19 lockdown measures and the Chinese Spring Festival (Fig. 3 red lines), much larger than the area-weighted daily PM$_{2.5}$ changes (5.1 µg m$^{-3}$). However, the PWE$_{HAP}$ increased by 18.1 µg m$^{-3}$ (95% CI, 14.1–22.5) during the same period, leading to a 5.1 µg m$^{-3}$ (95% CI: 1.1–9.5) increase in the IPWE (Fig. 3). The 95% confidence intervals are obtained by running 50,000 Monte Carlo simulations that considers the uncertainties in key factors that affect the PWE$_{AAP}$ change, including population migration, time-activity pattern and extra PM$_{2.5}$ exposure levels of solid-fuel users. The results indicate that the net increase in IPWE during the lockdown is robust. There are two main reasons for the large increase in PWE$_{HAP}$. First, the time people stayed indoors increases substantially by approximately 3.1 and 4.2 h per day in urban and rural areas, respectively, mainly caused by the COVID-19 lockdown, bringing a 12.1 µg m$^{-3}$ increase in PWE$_{HAP}$. This is reflected by the abrupt increase in PWE$_{HAP}$ near January 23 (the beginning of the lockdown) and the abrupt decrease near March 5 (the end of the lockdown) in Fig. 3. Second, the Spring Festival results in a 5.9 µg m$^{-3}$ increase in PWE$_{HAP}$, which was caused by an average of 44 million more people living in rural areas immediately after the return-to-home migration tide compared with the normal situation within our domain of interest (see Fig. S4), and a much higher fraction of solid fuel use in rural areas than in urban areas (see Fig. S4 for the fractions of populations using solid fuels). This effect is evidenced by the gradual increase of PWE$_{AAP}$ before the Spring Festival (January 25) and the subsequent much slower decrease after the Spring Festival in Fig. 4. Note that our estimated changes in the time spent indoors and the populations using solid fuels due to the lockdown are generally consistent with a 41% increase in household coal consumption shown by a recent survey, strengthening the robustness of our estimate of the change in PWE$_{AAP}$ during the lockdown (see Methods).

3.4. Air quality changes related to short-term health effects

The significant decreases in daily PWE$_{AAP}$ during the lockdown were expected to reduce the adverse effects of short-term PM$_{2.5}$ exposure. During the lockdown period in 2020, the total prevented deaths from all-cause mortality attributed to PWE$_{AAP}$ were 655 (95% CI: 446–833; Table 1), with the largest contribution from cardiovascular issues (total 346 (231–563) premature deaths due to daily PWE$_{AAP}$ (red lines, left axis), PWE$_{HAP}$ (black lines, left axis) and IPWE (green lines, right axis) in the NCP simulated by the model with the updated emission inventory during pre lockdown (January 1st-January 22nd), lockdowns (January 23rd—March 5th), and post lockdown (March 6th-31st), the hypothetical PM$_{2.5}$ in 2020 without considering the effect of the lockdown measures (dashed lines). The uncertainty ranges stand for the 95% confidence interval for the PWE$_{AAP}$ considering the population migration and duration of indoor activity (see Methods Section 2.3). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 3. The time series for the daily PWE$_{AAP}$ exposure (red lines, left axis), PWE$_{HAP}$ exposure (black lines, left axis) and IPWE exposure (green lines, right axis) in the NCP simulated by the model with the updated emission inventory during pre lockdown (January 1st-January 22nd), lockdowns (January 23rd—March 5th), and post lockdown (March 6th-31st), the hypothetical PM$_{2.5}$ in 2020 without considering the effect of the lockdown measures (dashed lines). The uncertainty ranges stand for the 95% confidence interval for the PWE$_{AAP}$ considering the population migration and duration of indoor activity (see Methods Section 2.3). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1 Short-term premature deaths due to daily PWE$_{AAP}$ and PWE$_{HAP}$ changes during the lockdown period in 2020 compared with hypothetical PM$_{2.5}$ concentrations without the lockdown in 2020. Negative values mean reduced premature deaths due to decreased PM$_{2.5}$ exposure (mainly PWE$_{AAP}$), and positive values mean added premature deaths due to increased PM$_{2.5}$ exposure (PWE$_{HAP}$ and IPWE).

| Cause of Death | RR (Chen et al., 2017) | RR (Atkinson et al. (2014)) |
|---------------|------------------------|-----------------------------|
| All-cause     | −655 (446–833)         | −3,103 (1,549–4,663)        |
| Cardiovascular| −372 (248–496)         | −1,160 (565–1,771)          |
| Respiratory   | −118 (69–170)          | −614 (410–819)              |
| All-cause     | 2,267 (1,547–2,884)    | 10,638 (5,344–15,822)       |
| Cardiovascular| 1,288 (859–1,716)      | 3,987 (1,954–6,052)         |
| Respiratory   | 407 (239–586)          | 2,094 (1,407–2,775)         |
| All-cause     | 609 (415–775)          | 2,860 (1,436–4,273)         |
| Cardiovascular| 346 (231–461)          | 1,072 (525–1,628)           |
| Respiratory   | 109 (64–158)           | 563 (378–747)               |
avoided 372 deaths, 95% CI: 248–496), when compared with the hypothetical 2020 simulation without considering COVID-19 lockdown measures on emission changes. Compared with the historical periods in the past three years (2017–2019), we determined that in NCP, 1,189 (95% CI: 810–1,515) prevented premature deaths were associated with ambient PM$_{2.5}$ improvements for all-cause mortality, with 57% of the total from cardiovascular disease and 18% associated with respiratory disease (Table S7). Our results are comparable to those of Chen et al. (2020a), who reported that 3,214 (95% CI: 2,340–4,087) prevented premature deaths associated with PM$_{2.5}$ improvements in mainland China, considering that the NCP in our study has approximately 0.69 billion people, almost half of the total population in China as analyzed in Chen et al. (2020a). By using the alternative CRF from Atkinson et al. (2017), we had much higher amount of prevented premature deaths, 3,103 (95% CI: 1,549–4,663 deaths, due to PWE$_{AAP}$ changes when compared to the no COVID-19 lockdown scenario, and 5,674 (2,821–8,560) deaths when comparing with 2017–2019 (see Tables S7 and S8), reflecting the uncertainties from the CRF. However, when we consider the increased indoor PM$_{2.5}$ exposure, we estimated that there would be 609 (95% CI: 415–775) more deaths due to the increased exposure to HAP, with the largest contribution from cardiovascular disease at 346 deaths 95% CI: 231–461); see Table 1. When using the alternative RR, the estimated additional deaths could reach 2,860 (95% CI:1,436–4,273). As discussed in Section 3.2, the added deaths were attributed to the increased indoor length and household energy source usage during lockdown, mainly in rural areas.

4. Discussion

COVID-19, as a natural disaster, also serves as a natural experiment to evaluate the various control policies for mitigating air pollution. Previous studies have already implied that lockdown measures during the pandemic could significantly drop the NO$_2$ concentration as well as other air pollutants, such as PM$_{2.5}$ and Oz. However, extreme events still occurred in China during the lockdown due to unfavorable meteorological conditions and highly nonlinear chemical regimes (Miyazaki et al., 2020; Le et al., 2020). Several studies have also associated improved air quality with avoided premature deaths in China and Europe (Chen et al., 2020a; Chen et al., 2020b; Giani et al., 2020). However, no studies have considered the effects of indoor exposure, which accounted for nearly 35% of premature deaths due to air pollution in 2019 (SOGA2020). Due to lockdown restrictions, people were confined to their homes; hence, HAP would become a major factor in determining the effect of COVID-19-related lockdown restrictions on the air quality to which people were exposed.

A comparison of the model performance statistics indicates the ability of the model to simulate PM$_{2.5}$ before and during lockdown. These criteria limits, although a good measure of model performance, should act more as a guideline instead of definitive tests since they are determined by simulations with limited temporal and spatial coverage (Zhang et al.,2014). Moreover, the high coefficient of correction for PM$_{2.5}$ (average R: 0.74) and Oz (average R: 0.71) and the time series plot in Fig. 1 indicate that the model can efficiently capture the daily variations.

Due to restrictions on population movement during the lockdown, outdoor activities were reduced to a great extent, resulting in reduced ambient air pollution. A comparison of the simulated scenarios before and during lockdown in 2020 indicated that PM$_{2.5}$ in the NCP was reduced by 9.7 µg m$^{-3}$, while it was reduced by 7.9 µg m$^{-3}$ when this scenario during lockdown was compared to the average of 3 years (2017–2019) during the same period, thus resulting in a 1.8 µg m$^{-3}$ effective reduction in PM$_{2.5}$ concentration due to lockdown. However, the simulated effect of the lockdown shows a trend that underestimates the actual reduction, which is estimated to be approximately 5.9 µg m$^{-3}$, which can be attributed to Chinese New Year starting on different days in 2017–2020 and hence making it difficult to fully decouple the effect. This indicates that the benefits of lockdown to ambient air quality were minor, and the same has also been depicted in other studies (Shi et al., 2021).

Previous studies have shown that a substantial decrease in HAP from household cooking and heating contributed significantly to the decreased PM$_{2.5}$ mortality burden in China (Zhao et al., 2018; Yun et al., 2020). However, as the migration of people from urban areas (areas with traditionally greater use of cleaner fuels) to rural areas (areas with use of cheaper and more dirty fuels) occurred during the Chinese Spring Festival, these dynamics started to shift. COVID-19-related lockdowns further compelled people to spend the majority of their time indoors, thus increasing the exposure time of people to HAP. The end result is that a larger number of people are exposed to HAP for a longer duration, thus increasing their health risk. Population-weighted exposure measures the actual benefit or loss due to changes in pollutant concentrations. PWE$_{AAP}$ in the NCP was 13.0 µg m$^{-3}$ lower in the lockdown scenario than in the hypothetical scenario of no lockdown during the same period, which was much greater than the reduction in area-weighted daily PM$_{2.5}$ change (5.1 µg m$^{-3}$) between the same scenarios. The same indicates a higher benefit of reduction in PM$_{2.5}$ in high-density population areas in cities during lockdown. PWE$_{AAP}$ on the other hand, increased by 23.9 µg m$^{-3}$ during lockdown when compared to the hypothetical scenario, while it increased by 15.2 µg m$^{-3}$ compared to the pre lockdown scenario, with rural PWE$_{AAP}$ registering even higher values of 24.2 µg m$^{-3}$. Note that in the hypothetical scenario, we assumed constant populated-weighted HAP exposure (Fig. 3 black dashed line) since we do not know the day-to-day variations of solid fuel usages, which could be one limitation in our study. PWE$_{AAP}$ was observed to be the dominant IPWE during lockdown, with values approximately 50–80% higher than before and after lockdowns. The IPWE effects on urban and rural populations indicate higher benefits in terms of exposure reduction in urban areas, probably due to the large-scale migration of people to rural areas during the Chinese New Year as well as the use of cleaner fuels for cooking and heating, while the increased population in addition to the use of solid fuels and additional time spent indoors during the New Year resulted in higher exposure among the rural population.

The reduction in PWE$_{AAP}$ due to lockdown also translated to health gains, with 655 (95% CI: 446–833) prevent deaths when compared to the hypothetical scenario of no lockdown during the same period. The health gains due to lockdown were even higher when compared to a 3-year averaged (2017–2019) PM$_{2.5}$ concentration during the same period with 1,189 (95% CI: 810–1,515) all-cause premature deaths prevented which is comparable to Chen et al. (2020a) and Chen et al. (2020b) which reported 3,214 (95% CI: 2,340–4,087) prevented premature deaths in mainland China during the same period considering that NCP has 0.69 million people which is half of that in mainland China. Cardiovascular (57%) and respiratory (18%) diseases form the majority of the diseases due to air pollution. The entire dynamics, however, changes when PWE$_{AAP}$ is taken into consideration, as it results in 2,267 (95% CI: 1,547–2,884) increased mortality with the highest addition of 1,288 (95% CI: 859–1,716) cardiovascular mortality. The effect of PWE$_{AAP}$ on IPWE is such that the effect of reduced PWE$_{AAP}$ is negated and the net effect results in added 609 (95% CI: 415–775) premature mortality. The use of alternative CRF from Atkinson et al. (2017) results in higher estimates of premature mortality in each case.

An assumption that may affect the calculated changes in ambient and household PM$_{2.5}$-related premature deaths is the relative toxicity of PM$_{2.5}$ from these two sources. In this study, we hypothesize that the health effects depend only on the inhaled amount of PM$_{2.5}$ and are independent of the sources and chemical composition, which appears reasonable in view of the available quantitative epidemiological studies. However, a large number of studies about the relative toxicity of different PM$_{2.5}$ compositions are divided. For example, some studies have reported that carbonaceous aerosols (black carbon and organic aerosol) could be significantly more toxic than other aerosol species.
The COVID-19 pandemic created a unique scenario in which outdoor activities by people were greatly reduced, resulting in a reduction in outdoor air pollution. However, the results above indicate that the reduced outdoor pollution did not translate to health gains, since extended exposure to dirty indoor air negated the effect of reduced outdoor pollution. This effect was more pronounced in rural China, where people have less access to cleaner household fuels. We acknowledge that there are uncertainties in our study in estimating indoor air pollution exposure; for example, we did not consider the Spring Festival holiday effect on the changes in indoor exposure. Another limitation in our study is that we only considered the exposure and health impact of PM, which is responsible for the largest number of premature deaths among all pollutants (Cohen et al., 2017; Lelieveld et al., 2015). Future studies are needed to evaluate the changes in the exposures and health impacts of other air pollutants, such as O₃ and NO₂. In our study, we did not consider the changes in the use of clean household fuels from 2018 to 2019 resulting from China’s newly launched rural residential solid fuel substitution campaign (Clean Heating Plan for Northern China in Winter for 2017–2021), which would likely reduce our estimates of indoor household exposure by 19% (Meng et al., 2019). However, from our results we argue that exposure to indoor air pollution, especially for people in rural areas, is comparable to, if not larger than ambient air pollution exposure and should not be neglected. This natural pandemic experiment is a clear indication that clean air policies need to be mutually inclusive of outdoor and indoor air quality, since any neglect of indoor air quality will negate the benefits of clean outdoor air. Thus, to truly realize the benefits of China’s National Air Quality Action Plan, indoor air pollution, specifically amongst the rural population, needs to be prioritized. There is an urgent need for the government to strictly implement policies to encourage the rural population to shift from solid fuel to cleaner fuels.

Credit authorship contribution statement
Yiqi Zhang, Bin Zhao, Yueqi Jiang: Conceptualization, Methodology, Formal analysis, Validation, Data curation, Writing – original and revised draft. Jia Xing: Conceptualization, Supervision, Project administration, Funding acquisition. Shovan K. Sahu: Writing – original and revised draft. Hao Tian Zheng, Dian Ding, Suzhen Cao, Liqiong Hao, Cong Yan, Xiaoli Duan, Jingnan Hu, Jinghao Hao: Resources, Data curation, Writing – original draft. Shuxiao Wang: Conceptualization, Supervision, Project administration, Funding acquisition, Writing – review & editing.

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 material
Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2021.106918.

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