

## Spring festival and COVID-19 lockdown

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# Geophysical Research Letters

## RESEARCH LETTER

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### Special Section:

The COVID-19 pandemic: linking health, society and environment

### Key Points:

- The Chinese Spring Festival led to a 14.1% decrease in NO<sub>2</sub>, 6.6% increase in O<sub>3</sub> and a mixed effect on PM<sub>2.5</sub> across China in 2015–2019
- The 2020 lockdown resulted in –15.4%, –17.0%, –14.5%, –7.6%, –9.7%, and +24.6% changes for NO<sub>2</sub>, SO<sub>2</sub>, CO, PM<sub>10</sub>, PM<sub>2.5</sub>, and O<sub>3</sub>, respectively
- Fireworks emissions contributed to haze in many cities such as an additional 29 μg m<sup>–3</sup> PM<sub>2.5</sub> in Beijing on the first lunar day of 2020

### Supporting Information:

Supporting Information may be found in the online version of this article.

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## Spring Festival and COVID-19 Lockdown: Disentangling PM Sources in Major Chinese Cities

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**Abstract** Responding to the 2020 COVID-19 outbreak, China imposed an unprecedented lockdown producing reductions in air pollutant emissions. However, the lockdown driven air pollution changes have not been fully quantified. We applied machine learning to quantify the effects of meteorology on surface air quality data in 31 major Chinese cities. The meteorologically normalized NO<sub>2</sub>, O<sub>3</sub>, and PM<sub>2.5</sub> concentrations changed by –29.5%, +31.2%, and –7.0%, respectively, after the lockdown began. However, part of this effect was also associated with emission changes due to the Chinese Spring Festival, which led to ~14.1% decrease in NO<sub>2</sub>, ~6.6% increase in O<sub>3</sub> and a mixed effect on PM<sub>2.5</sub> in the studied cities that largely resulted from festival associated fireworks. After decoupling the weather and Spring Festival effects, changes in air quality attributable to the lockdown were much smaller: –15.4%, +24.6%, and –9.7% for NO<sub>2</sub>, O<sub>3</sub>, and PM<sub>2.5</sub>, respectively.

**Plain Language Summary** Strict lockdown measures imposed in most countries to stop the 2020 COVID-19 pandemic spread, led to changes in air pollutant concentrations. The lockdown in China started at the start of the Chinese Spring Festival (CSF), making it difficult to disentangling the lockdown from the CSF effects. We applied a machine learning meteorological normalization technique that considered the effects of lunar holidays that fall on different Gregorian dates in different years and accounted for meteorological effects on surface air quality. We found that the normal CSF in 2015–2019 led to reproducible changes in NO<sub>2</sub> (–14.1%) and O<sub>3</sub> (+6.6%) concentrations, and a mixed effect on PM<sub>2.5</sub> across China. After decoupling the CSF effects, the 2020 lockdown produced limited changes in air quality. Thus, measures similar to the COVID-19 lockdown will suffice to reduce NO<sub>2</sub> levels in China to be below WHO guidelines but unlikely to attain the WHO PM<sub>2.5</sub> guidelines. This methodology permits estimation of traditional holiday- and event-driven air quality changes, especially when there are recurring cultural events based on non-Gregorian dates that may overlap with intervention.

## 1. Introduction

The COVID-19 outbreak changed the world and created global concerns regarding public health, global economy, human behavior, social networks, and air quality (Amouei Torkmahalleh et al., 2021; Chakraborty & Maity, 2020; Diffenbaugh et al., 2020; Rodríguez-Urrego & Rodríguez-Urrego, 2020; Venter et al., 2020). Wuhan was the first pandemic epicenter and imposed an unprecedented lockdown beginning January 23, 2020. China was subsequently placed into a lockdown. These restrictions interrupted a wide array of economic activities thereby reducing primary air pollutant emissions. The unexpected pollutant emission reductions created a unique opportunity to assess the responses of air quality to rapid temporary reductions in anthropogenic emissions, and inform future air quality abatement strategies.

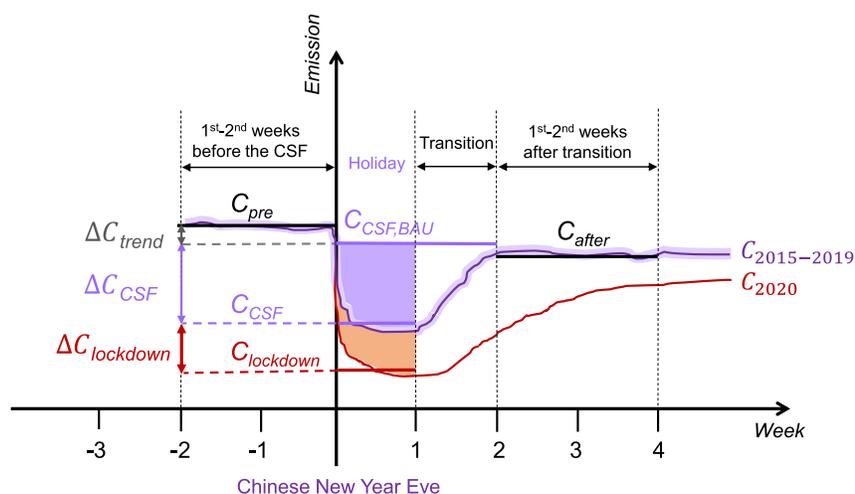
Many early studies showed substantial declines in observed concentrations of nitrogen dioxide (NO<sub>2</sub>) during lockdown periods globally (Chakraborty & Maity, 2020; Cole et al., 2020; Gkatzelis et al., 2021; He et al., 2020; Lee et al., 2020; Liu et al., 2020; Patel et al., 2020; Pei et al., 2020; Venter et al., 2020). The observed changes resulted from both meteorology and emission changes (Grange & Carslaw, 2019; Gkatzelis

et al., 2021). To account for the effects of meteorology and emission trends, so-called “deweathering” and “detrending,” respectively, were used to estimate the short-term interventions (e.g., lockdown) effects on air pollution. Comparisons of observations during the lockdown with the same calendar period in previous years were extensively reported (Patel et al., 2020; Pei et al., 2020; Shi & Brasseur, 2020; Sicard et al., 2020). That approach assumed negligible interannual variations in the pollutant emissions and meteorology. In cities where clean air actions are in place emissions are likely to have been trending downward as a result of the regulatory actions (Vu et al., 2019; Zhang et al., 2020). Some studies have analyzed the air quality changes with adjustments for meteorology using air quality models (e.g., Le et al., 2020; Wang et al., 2021; Zhao et al., 2020). The limited availability of up-to-date emissions inventories introduced substantial uncertainty into the estimation of the air quality responses to lockdown measures. Traditionally, deweathering can be achieved by regression analysis (Liang et al., 2015; Zheng et al., 2021), but the performance of such regression models is usually not robust (Venter et al., 2020). Machine learning offers an alternative, more accurate method to deweather (Grange & Carslaw, 2019; Grange et al., 2018; Lovric et al., 2021; Petetin et al., 2020; Rybarczyk & Zalakeviciute, 2021; Vu et al., 2019). Gkatzelis et al. (2021) critically reviewed the various available statistical approaches used for deweathering and detrending in evaluating the lockdown impacts on air pollution.

Shi et al. (2021) applied a machine learning method to globally deweather air pollutants concentrations in 11 cities. They recognized the importance of detrending when evaluating air quality changes due to interventions such as lockdowns. However, the detrending method based on Gregorian dates by Shi et al. (2021) introduces an uncertainty in the counterfactual (business as usual: BAU) scenario if there were particular events, such as Chinese lunar Spring Festival (CSF) or Easter Holidays, which have different Gregorian dates in different years. The beginning of the 2020 lockdown overlapped with the CSF. CSF, the most important Chinese national holiday, encompasses one week that includes over 30 billion trips across China since many people move from megacities to their hometowns, making “empty cities” during CSF a unique phenomenon in Chinese megacities. Significant declines in primary particles and  $\text{NO}_x$  in urban areas termed holiday effects (Lai & Brimblecombe, 2017) occurred due to reduced transportation and some industries (Jiang et al., 2015; Tanvir et al., 2021). Such holiday effects make it challenging to separate the lockdown changes from the CSF effects.

To address this challenge, Wang et al. (2021) combined in situ observations complemented by satellite measurements and air quality modeling to decouple  $\text{NO}_2$  changes attributable to the lockdown from the CSF effects and meteorology. In that study, 11-days moving average  $\text{NO}_2$  was used to compare the concentrations in 2020 with counterfactual levels, potentially biasing the results by smoothing the sudden changes after the lockdown/CSF start. Excluding the CSF-period data is an alternative (Zheng et al., 2021), but such exclusion would lead to the loss of some information.

We specifically addressed this issue by meteorologically normalizing major surface air quality data first, and then corrected the CSF effect to obtain real changes in air pollutants attributable to COVID-19 lockdown. We applied a machine learning-based meteorologically normalization (deweather) procedure to decouple meteorological impacts on air pollutant concentrations collected from over 300 surface air quality data measured in 31 provincial capital cities in mainland China from 2015 to 2020 (see Section 2). We improved our model performances by considering the exceptional (aperiodic in Gregorian calendar) emissions from the CSF that were not considered in prior relevant studies (Cole et al., 2020; Vu et al., 2019; Shi et al., 2021; Table S1). The percentage change ( $P$ ) of the meteorologically normalized concentrations of an air pollutant during the CSF with respect to their BAU values in each individual year were estimated (deweathered and detrended Shi et al., 2021) (see Figure 1). The average change from 2015 to 2019 was considered as the CSF effects ( $P_{CSF}$ ). Thus, the additional effects of lockdown measures on air quality can be isolated by subtracting the CSF effects from the overall changes in 2020. This approach enabled the quantification of the impacts of the COVID-19 lockdown as well as the CSF holidays on the air quality changes.



**Figure 1.** Concept of the calculation for the effects of Chinese Spring Festival holiday and additional lockdown by taking meteorologically normalized  $\text{NO}_2$  as an example.  $C_{2015-2019}$  and  $C_{2020}$  are the meteorologically normalized  $\text{NO}_2$  concentrations in 2015–2019, and 2020, respectively.  $C_{pre}$  and  $C_{after}$  are the average concentrations of  $\text{NO}_2$  in the 1<sup>st</sup>–2<sup>nd</sup> weeks before the lunar new year and 3<sup>rd</sup>–4<sup>th</sup> weeks after the lunar new year.  $C_{CSFB}$  and  $C_{CSFB,BAU}$  are the average value of  $\text{NO}_2$  during the CSF holiday and counterfactual  $\text{NO}_2$  under BAU emission scenario.  $\Delta C_{trend}$ ,  $\Delta C_{CSFB}$ , and  $\Delta C_{lockdown}$  are the changes in meteorologically normalized concentrations of  $\text{NO}_2$  attributable to the emissions trend, holiday effects, and additional lockdown effects, respectively.

## 2. Materials and Methods

### 2.1. Data Sources

Six criteria air pollutant concentrations ( $\text{SO}_2$ ,  $\text{NO}_2$ ,  $\text{CO}$ ,  $\text{O}_3$ ,  $\text{PM}_{10}$ , and  $\text{PM}_{2.5}$ ) in 2015–2020 for the 31 major Chinese cities in mainland China were collected from the China National Environmental Monitoring Center website (<http://106.37.208.233:20035>). Surface meteorological variables (air temperature, relative humidity, wind direction, wind speed, and pressure recorded at the airport of the selected cities) were downloaded from NOAA using the “worldMet” R package (<https://github.com/davidcarslaw/worldmet>). The boundary layer height, total cloud cover, surface net solar radiation, and total precipitation for every hour were collected from ERA5 reanalysis dataset. For each city, 72-hour backward air mass trajectories for every hour were calculated using the HYSPLIT model (Stein et al., 2015; Tanvir et al., 2021) with arrival height of 100 m a.g.l for the studied periods. Trajectories for each city were subjected to cluster analysis using the Euclidian distance to produce 12 clusters for analysis.

### 2.2. Random Forest Modeling and Meteorological Normalization

A machine learning-based meteorological normalization method using the random forest (RF) algorithm (Cole et al., 2020; Grange & Carslaw, 2019; Shi et al., 2021; Vu et al., 2019) was used to decouple the meteorological impacts on the observed air pollutants. As one of the best machine learning algorithm in building predictive models, RF can well capture the variation of air pollutants and better than air quality modeling (Grange et al., 2018; Vu et al., 2019). The explanatory variables including the meteorological variables, air mass clusters, and time variables were used to build the RF model and predict the air pollutant concentrations. Air pollutants either emitted from routine sources or formed via secondary formation periodically varied by time of day, day of week, and season, time variables such as Unix time (number of seconds since January 1, 1970), Gregorian day (day of the year), weekday, and hour of the day were used as surrogates of the trends of emissions strength. Local air pollution is affected by regional transport. The air mass trajectory clusters provide likely directions of the potential source regions for a given city. The aforementioned variables are used as typical input features in previous studies (Cole et al., 2020; Grange et al., 2018; Shi et al., 2021; Vu et al., 2019). We included the lunar day as an additional time variable to account for the emission changes from lunar holidays. Model performances were improved if the lunar day was an added variable (Table S1 and Figure S3). For each pollutant in the 31 cities, the meteorological normalized

concentration at a particular hour was calculated by averaging 1,000 predictions from the meteorological variables (excluding all time variables) randomly resampled from the observation period (2015–2020). By comparing our results with those of Shi et al. (2021) (Figure S3), we successfully captured the effects of the CSF by including the lunar date. Further details regarding the RF model setting and meteorological normalization procedure are available in supporting information Text S1.

### 2.3. Quantifying Changes in Air Quality Attributable to the CSF and Lockdowns

We first compared the averaged meteorologically normalized air pollutant concentrations in the two weeks (1<sup>st</sup>–2<sup>nd</sup> weeks) before CSF with those in the 3<sup>rd</sup>–4<sup>th</sup> weeks after the CSF began. Using linear interpolation, half of the differences were then attributed to the counterfactual, BAU concentrations ( $C_{CSF,BAU}$ ) during the CSF holiday. The CSF holiday effects for the year of  $i$ ,  $P_{CSF,i}$ , can be calculated as the percentage change ( $P$ ) of pollutant concentrations during the CSF holiday with respect to their BAU levels ( $C_{CSF,BAU}$ ).  $P_{CSF,i}$  in each city may vary by year due to emission changes. The CSF holiday effects for each pollutant in each city were estimated by averaging  $P_{CSF,i}$  values from 2015 to 2019 (Figure 1).

$$P_{CSF} = \frac{1}{5} \sum \left[ \frac{\overline{C_{CSF,i}}}{\left( \frac{\overline{C_{pre,i}} + \overline{C_{after,i}}}{2} \right)} - 1 \right] \times 100\% \quad (1)$$

where  $\overline{C_{pre,i}}$ ,  $\overline{C_{CSF,i}}$  and  $\overline{C_{after,i}}$  are the average concentrations in the 1<sup>st</sup>–2<sup>nd</sup> weeks before the holiday, during the holiday, and in the 2<sup>nd</sup>–3<sup>rd</sup> weeks after the holiday in year  $i$ , respectively. The day of the lunar New Year Eve was considered as a transition day before the CSF began. A 1-week transition period from the end of the CSF holiday to the Lantern Festival was also included.

We selected the equivalent 1-week CSF holiday rather than the whole lockdown period in each city as episode candidates for calculation. The 2020 changes in air pollutants during the CSF were attributed to the effects of trend, holiday, and lockdown measures (Figure 1). The percentage change in the trend of each pollutant in 2020 was estimated by averaging its percentile changes from 2015 to 2019. Thus, the percentage changes caused by lockdown measures alone can be estimated as:

$$P_{lockdown} = P - P_{trend,2020} - P_{CSF} = \frac{\overline{C_{CSF,2020}}}{\overline{C_{pre,2020}} \times \left( 1 - \frac{1}{5} \sum [C_{CSF,BAU_i} / C_{pre,i} - 1] \right)} - 1 \quad (2)$$

where  $\overline{C_{CSF,2020}}$  is the average concentration during the CSF holiday in 2020. Details of the estimations of the CSF and lockdown effects are presented in the Text S2.

## 3. Results and Discussion

### 3.1. Changes in Air Quality Attributable to the CSF in 2015–2019

The observed daily concentrations of ambient NO<sub>2</sub>, O<sub>3</sub>, PM<sub>2.5</sub>, SO<sub>2</sub>, CO, and PM<sub>10</sub> are presented in Figures S4–S9. A sudden decline in the meteorologically normalized NO<sub>2</sub> coincided with the start of the CSF in all studied cities in 2015–2019 (Figure S10), with an average  $P_{CSF}$  of –14.1%, ranging from –24.1 ± 2.0% in Hangzhou to –3.9 ± 1.1% in Harbin (Table S2). A recent study reported that the CSF effect caused a 20.9% reduction of the NO<sub>x</sub> emission intensity (Gg/d) in China in 2019 (Zheng et al., 2020), comparable to our estimates of NO<sub>2</sub> in 2019 (14.7 ± 6.5%). On average, O<sub>3</sub> increased by 6.6% (from +1.5 ± 3.4% in Lhasa to +10.0 ± 1.4% in Changchun) (Figure S11). Meteorologically normalized PM<sub>2.5</sub> increased at midnight of the lunar New Year Eve in more than half of the studied cities (18 out of 31, Figure 2), with  $P_{CSF}$  ranging from –9.1 ± 4.2% in Hangzhou to +24.9 ± 4.2% in Hohhot. Fireworks are likely the source since they produce particles as well as SO<sub>2</sub> and NO<sub>2</sub> (Wang et al., 2007). The meteorologically normalized SO<sub>2</sub>, CO, and PM<sub>10</sub> are presented in Figures S12–S14. A decline in meteorologically normalized SO<sub>2</sub> during the CSF was also observed in most cities, with an average  $P_{CSF}$  of –3.4% (–17.4 ± 6.1% in Guangzhou to +13.6 ± 17.2% in Beijing). The average changes in the meteorologically normalized CO were –2.3% (from –8.0 ± 2.9% in

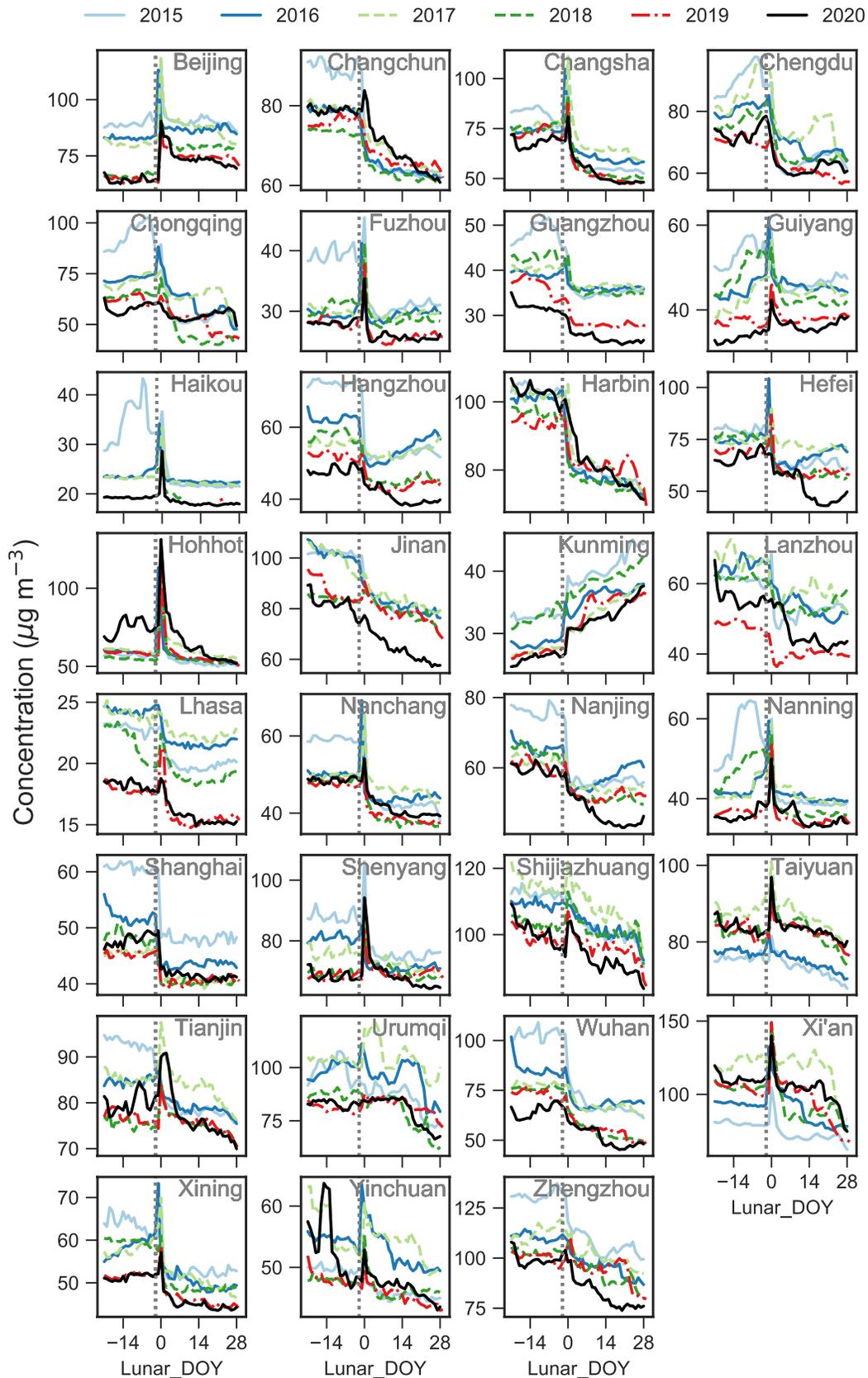


Figure 2

Lanzhou to  $+5.1 \pm 5.3\%$  in Taiyuan). Meteorologically normalized  $PM_{10}$  had a similar trend to  $PM_{2.5}$ , with an average  $P_{CSF}$  of  $-0.5\%$ .

The changes in meteorologically normalized  $NO_2$  values were smaller than the measured data (see Table S2 and discussion in supporting information Text S3). Similar results were obtained for the other air pollutants, suggesting that meteorological variations played a major role in the short-term variability of the air pollutant concentrations during the CSF. The responses of the observed air pollutants to the CSF were partially masked by the meteorological variations. Thus, they do not necessarily provide the signs and magnitudes of changes in source emissions. The  $P_{CSF}$  have much smaller standard deviations than  $P_{obs}$  (Table S2), demonstrating that the responses of air quality to emissions changes remain constant across the studied years.

The declines in  $NO_2$  were strongly related to transportation and industrial emission changes as determined by the changes in anthropogenic emissions in February 2019 in mainland China (Zheng et al., 2020). Such effects of CSF on  $NO_2$  were more substantial for cities with greater vehicle populations (Figure S15). Decreases in meteorologically normalized  $NO_2$  and corresponding increases in  $O_3$  were ubiquitous across all these cities in China. The decreased traffic volume caused reduced  $NO$  emissions and likely led to a decline in local titration of  $O_3$  (Sicard et al., 2020), contributing to a sharp increase in  $O_3$  during the CSF holiday. This result is also in phase with existing literature that the decreased  $NO_x$  emission over east China due to the lockdown led to a significant increase in surface  $O_3$  and other atmospheric oxidants ( $HO_2$ ,  $NO_3$ , and OH radical) through air quality modeling and measurements (Huang et al., 2020; Lv et al., 2020; Zhang et al., 2021).

The substantial spike in meteorologically normalized  $PM_{2.5}$  that appeared immediately at midnight (around 12:00 a.m.) of each lunar New Year Eve was largely attributed to the CSF-related emissions (Jiang et al., 2015; Lai & Brimblecombe, 2017, 2020). Fireworks are a ubiquitous worldwide festival events such as both the CSF and Lantern Festival in China (Dai et al., 2020; Lai & Brimblecombe, 2020; Pang et al., 2021; Tian et al., 2014; Wang et al., 2007), the Las Fallas in Spain (Moreno et al., 2007), and the Guy Fawkes celebrations in UK (Godri et al., 2010). Fireworks emissions are a temporary source that can substantially exacerbate air pollution and remain airborne for several days (Godri et al., 2010; Kong et al., 2015; Moreno et al., 2007; Tian et al., 2014). As the most important festival in China, most people return to their hometown to celebrate the CSF with activities including igniting fireworks on New Year's Eve. "Sheng Wang Huo" is a tradition in Shanxi, Hebei, and Inner Mongolia Provinces to celebrate the CSF by igniting a bonfire of stacked coal/wood and burned over five days (Dai et al., 2020). Therefore, emissions from these festival-related sources tend to offset the effects of halted traffic and economic activities during the CSF (Lai Y & Brimblecombe, 2017; Sun et al., 2020; Dai et al., 2021). To reduce emissions, these events were increasingly banned by local governments in many megacities, particularly after 2017. Guangzhou was the first Chinese city to implement a no-fireworks policy in urban areas starting in the early 1990s (Jiang et al., 2015). Thus, the meteorologically normalized  $PM_{2.5}$  in Guangzhou in the studied years did not show a spike after the CSF beginning (Figure 2). Nanjing had fireworks problems in earlier years (Kong et al., 2015). The local government then imposed stricter control of fireworks beginning January 1, 2015, which has been effective at improving air quality as reported previously (Lai & Brimblecombe, 2017). This regulatory ban was consistent with our result (Figure 2) as there was no obvious spike in the meteorologically normalized  $PM_{2.5}$  in Nanjing as observed in other cities across 2015–2020. Shanghai was similar. For Beijing, Fuzhou, Hohhot, Nanning, Tianjin, and Xi'an, meteorologically normalized  $SO_2$  also increased concurrently with the increase of meteorologically normalized  $PM_{2.5}$  at the midnight of the lunar New Year Eve (Figure S12) and decreased afterward, further supporting that the sharp spike of  $PM_{2.5}$  was from fireworks emissions implying that the increased  $PM_{2.5}$  in those cities originates primarily from the surrounding rural areas. Although fireworks were generally banned in urban areas, people still shoot fireworks in rural areas where coal/biomass were extensively burned for heating/cooking.

Several studies found that high particulate haze events in China during the lockdown were driven by enhanced secondary pollution offsetting the primary emissions reductions (Chang et al., 2020; Sun

**Figure 2.** Meteorologically normalized concentrations of daily  $PM_{2.5}$  in the 31 major Chinese cities before and after the Chinese Spring Festival (CSF) in 2015–2020. Data are temporally aligned according to their lunar calendar dates in 2015–2020 and shown as Day of Year in Lunar calendar. Vertical dash line refers to the day before the CSF.

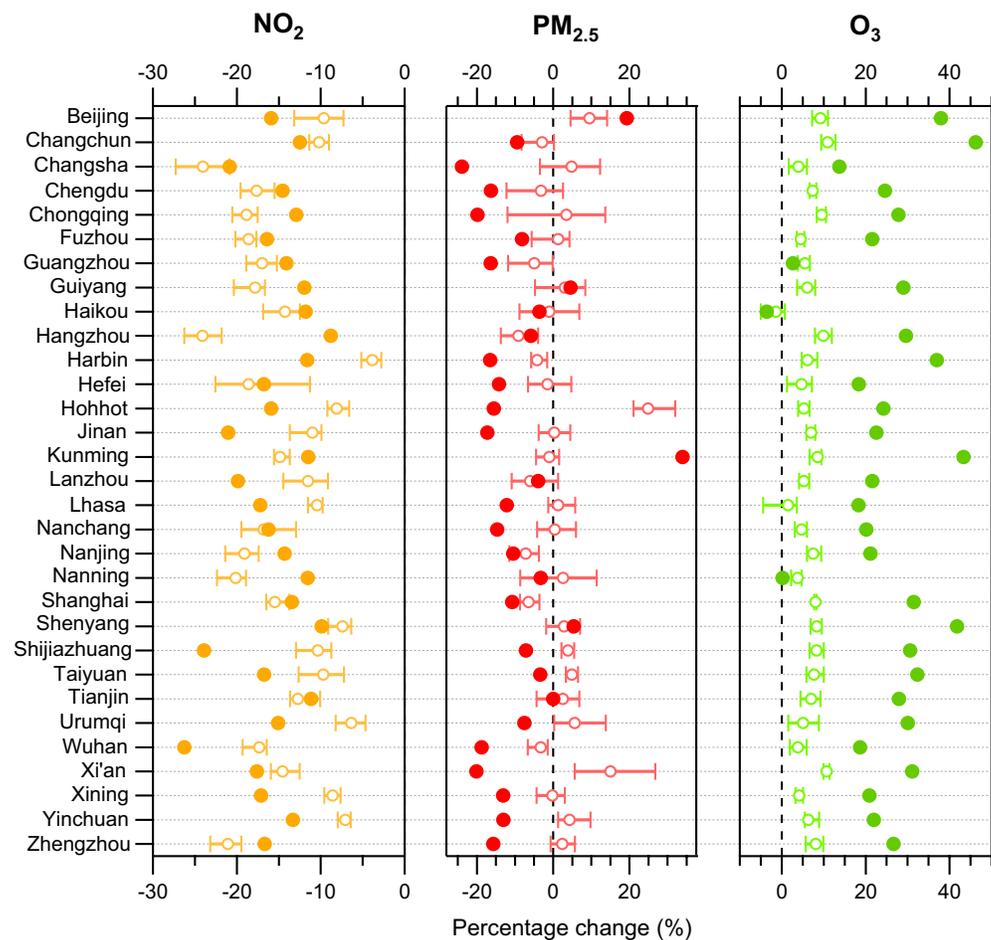
et al., 2020; Huang et al., 2020). If atmospheric oxidants increase substantially in urban areas, they may promote the secondary aerosol formation. However, total oxidants ( $O_3 + NO_x$ ) did not change significantly in Beijing (Shi et al., 2021). Furthermore, it is unlikely to have secondary  $PM_{2.5}$  increasing as sharp as the meteorologically normalized  $PM_{2.5}$  showed in most studied cities (Figure 2). Given that secondary aerosol was generally formed via various pathways under given meteorological conditions (e.g., high relative humidity), the calculated meteorologically normalized  $PM_{2.5}$  was a concentration averaged by 1,000 predictions with randomly sampled meteorological conditions, which tends to smooth the secondary  $PM_{2.5}$ . Our analysis suggests that the festival-related emissions (e.g., fireworks emissions) also played an important role in haze formation in a number of cities. In cities such as Hohhot, Xi'an, Shenyang, Taiyuan, Nanjing, and Haikou where the abrupt increase in meteorologically normalized  $PM_{2.5}$  occurred after midnight of New Year Eve, this excess  $PM_{2.5}$  likely originated from the festival-related emissions. The meteorologically normalized  $PM_{2.5}$  on the first lunar day of 2020 in those cities had elevated daily mass concentrations of 54.6, 26.2, 25.4, 13.8, 10.9, and  $8.6 \mu\text{g m}^{-3}$ , respectively, compared to a day before (Figure 2). For Beijing, we estimated that such festival-related emissions contributed 23.6, 29.1, 36.4, 24.2, 22.9, and  $29.1 \mu\text{g m}^{-3}$  daily  $PM_{2.5}$  for 2015 to 2020, respectively, based on meteorologically normalized values. These values are substantially below those estimated by the observed concentration in Beijing (Lai & Brimblecombe, 2020) because the meteorology limited the local dispersion of fireworks aerosol.

After the CSF ended, meteorologically normalized  $NO_2$  gradually returned to the pre-CSF levels as normal economic activities and local transportation resumed. In Hangzhou, a city without apparent fireworks emissions (Xu et al., 2020),  $PM_{2.5}$  dropped immediately after the CSF began and then returned to their pre-CSF level after the CSF ended. In contrast to the other cities, meteorologically normalized  $PM_{2.5}$  in Kunming, a southwestern city with more deleterious particulate pollution in spring than in other seasons, continuously increased from winter to spring that may result from its unique climatology. Thus, the CSF holiday led to generally reduced  $NO_2$  but increased  $O_3$  concentrations. Alternatively, changes in meteorologically normalized  $PM_{2.5}$  varied by city due to differences in CSF-related emissions and the extent of secondary aerosol formation.

### 3.2. Changes in Air Quality During CSF in 2020

Wuhan, the initial epicenter of the pandemic, had a major decline in meteorologically normalized  $NO_2$  ( $\sim 43.6\%$ ) and  $PM_{2.5}$  ( $\sim 22.0\%$ ), and an increase of  $\sim 22.5\%$  in  $O_3$ . Meteorologically normalized  $NO_2$  dropped to its lowest value on January 28 ( $28 \mu\text{g m}^{-3}$ , a reduction of  $\sim 42\%$  ( $P$ ) in  $NO_2$  from pre-lockdown levels). Our estimated change in meteorologically normalized  $NO_2$  was smaller than from the observed data ( $\sim 57\%$ ) (Pei et al., 2020; Sicard et al., 2020) and the meteorologically normalized data ( $\sim 63\%$ ) (Cole et al., 2020) without considering the lunar date variable, demonstrating the importance of separating the lockdown changes from the effects of meteorology and the CSF. In addition to the enforcement of the first-level emergency response on 25 January, Urumqi adopted an upgraded lockdown (home quarantine in communities and the whole city) beginning on 5 February (equivalent to lunar 12 January) to further prevent the transmission of the virus. The meteorologically corrected  $NO_2$  declined again on 6 February after its initial drop on the first day of the CSF (Figure S10).

Compared to the changes during the CSF in 2015–2019, the meteorologically normalized  $NO_2$  in 2020 declined more dramatically for all studied cities. The results suggest that the strict nationwide lockdown measures introduced additional air quality changes beyond the normal CSF reductions. Changes in meteorologically normalized  $NO_2$  ranged from  $-44.9\%$  in Changsha to  $-15.5\%$  in Harbin, with an average of  $-29.5\%$ . Accordingly, the meteorologically normalized  $O_3$  increased by  $31.2\%$  on average, ranging from  $-5.0\%$  in Haikou to  $+57.2\%$  in Changchun. Similar to previous years,  $O_3$  increased immediately on the first day of each lunar new year in all cities except Haikou. The direction and magnitudes of the changes in  $PM_{2.5}$  are heterogeneous across China. Changes in meteorologically normalized  $PM_{2.5}$  ranged from  $-22.0\%$  in Wuhan to  $+32.9\%$  in Kunming, with an averaged  $P_{\text{CSF}}$  of  $-7.0\%$ .



**Figure 3.** Percentage changes in meteorologically normalized NO<sub>2</sub>, PM<sub>2.5</sub>, and O<sub>3</sub> attributable to the Chinese Spring Festival (CSF) effects in 2015–2019 and additional lockdown effects in 2020. Open circles denote the average changes resulted from the CSF effects in 2015–2019, with error bars indicate the minimum and maximum values. The solid circles denote changes attributable to additional lockdown effects.

### 3.3. Changes in Air Quality Attributable to the Lockdown

The average change in meteorologically normalized NO<sub>2</sub> from the lockdown was –15.4% across all studied cities (Figure 3). Reduction of meteorologically normalized NO<sub>2</sub> in Wuhan (–26.3%) was below a previously reported value at urban background site (–44%) without the adjustment for CSF (Shi et al., 2021). Except for Haikou (–3.6%), meteorologically normalized O<sub>3</sub> attributable to the lockdown on average increased +25.8%. The average change in PM<sub>2.5</sub> attributable to the lockdown was –9.7%. The lockdown also led to –17.0%, –14.5%, and –7.6% changes for SO<sub>2</sub>, CO, and PM<sub>10</sub>, respectively. The overall changes in meteorologically normalized NO<sub>2</sub> and O<sub>3</sub> in all studied cities in the first week after the 2020 CSF began were 1.1 and 3.9 times the changes (same direction) during the CSF in 2015–2019. The meteorologically normalized PM<sub>2.5</sub> during the CSF shifted from increases in the CSF of 2015–2019 to decreases in the CSF of 2020. These results demonstrated that the mandatory lockdown measures amplified the CSF effects resulting from the festival-related emission reductions.

The responses of air quality to the lockdown estimated in this study differ substantively from existing reports (Chen et al., 2020; Cole et al., 2020; He et al., 2020; Liu et al., 2020; Pei et al., 2020; Shi & Brasseur, 2020; Sicard et al., 2020; Venter et al., 2020). The reason for the differences is that we decoupled meteorology and the confounding CSF effects from lockdown-induced changes. This decoupling approach provided more reliable estimates of the air quality responses to the lockdowns, which is important for understanding

lockdown effects for policy assessment. The limitations of the methodology are presented in supporting information Text S4.

The effects of holiday on air quality were observed worldwide. Our findings also have implications for other locations in other countries that follow similar Chinese traditions, and countries with localized cultural activities based on non-Gregorian dates, such as Diwali (India national calendar) (Perrino et al., 2011), Jewish Day of Atonement (Levy, 2013), festivals of Islam, and the Easter holiday (the exact date for Easter holiday is tied to the vernal equinox). By including their specific calendar as a predictor variable in the model, it is likely that lunar date will capture holiday effects of related cultural events that reduce or enhance primary emissions.

#### 4. Policy Implications for Air Pollution Control

Reductions from anthropogenic emissions (particularly transportation sector) during CSF/lockdown resulted in significantly lower  $\text{NO}_2$  in all studied capital cities of mainland China. The meteorologically normalized daily  $\text{NO}_2$  in all provincial capital cities were below the daily limit value (i.e.,  $80 \mu\text{g m}^{-3}$  for daily  $\text{NO}_2$ ) of the national ambient air quality standards of China (NAAQS, GB3095-2012) (MEE, 2012). Emissions reductions on the scale of the lockdown overlapping the CSF were insufficient for most of the cities to bring the daily  $\text{PM}_{2.5}$  concentrations into compliance with the WHO guidance level (WHO, 2006) (i.e.,  $25 \mu\text{g m}^{-3}$  for daily  $\text{PM}_{2.5}$ ). This result could be expected because most emission reductions during the lockdown came from transportation and some industrial emissions sectors (such as nonessential industrial production) that account for only a small proportion of primary  $\text{PM}_{2.5}$  emissions in China (Li et al., 2018). Emissions from industrial activities and residential solid fuel continue to be the major sources of air pollution in China given its industry-dominated emissions and coal-dominated energy consumption (Li et al., 2018; Zhang et al., 2019; Zhao et al., 2018). It suggests that a large fraction of sulphate, a major species of  $\text{PM}_{2.5}$ , was from residential coal combustion (Dai et al., 2019; Hopke & Dai, 2021). There is also an urgent need to control another increasingly important secondary pollutant,  $\text{O}_3$ , in China. Given the nonlinear relationship between secondary pollutants and their precursor gaseous in atmosphere (Seinfeld & Pandis, 2016), it is crucial to adopt synergistic reduction strategies to simultaneously curb both VOCs and  $\text{NO}_x$  emissions, to slow the increasingly enhanced secondary  $\text{PM}_{2.5}$  and  $\text{O}_3$  pollution in the future.

A decreasing interannual trend of meteorologically normalized air pollutant concentrations provided a measure of the effectiveness of abatement measures. The meteorologically normalized  $\text{SO}_2$  before the start of the CSF also decreased year by year, particularly in the Beijing-Tianjin-Hebei and surrounding areas after 2017 when the central and local governments enacted an extensive program of replacing the solid fuels with natural gas and electricity (Wang et al., 2020). The success of the Clean Air Action and other control measures was also evident from the decreased meteorologically normalized  $\text{PM}_{2.5}$  and  $\text{NO}_2$  before the CSF in 2015–2019 in most provincial capital cities. Although the air quality in northern China has improved considerably since 2013 (Zhang et al., 2019), the air pollution in the Fenhe-Weihe basin (Taiyuan and Xi'an urban agglomerations) has deteriorated over the past years (Song et al., 2017). The meteorologically normalized  $\text{NO}_2$  in Taiyuan, Xi'an, Lanzhou, and Xining were higher in recent years than those in 2015–2016. Similarly, meteorologically normalized  $\text{PM}_{2.5}$  in Taiyuan and Xi'an were higher in 2019–2020 compared to previous years. Although the current “Blue Sky Protection Campaign” was implemented by the central government in 2018, more aggressive efforts are needed to further reduce  $\text{NO}_2$  in these areas.

Changes in air quality attributable to the lockdown measures were smaller than expected when adjusted for other effects (Shi et al., 2021). Our results also highlight that a larger decline in  $\text{NO}_x$  emissions potentially risks increased  $\text{O}_3$  pollution in most megacities (Grange et al., 2021). The health benefits from COVID-19 lockdown measures were compromised since the  $\text{NO}_2$  and  $\text{PM}_{2.5}$  reductions might be offset by increased  $\text{O}_3$ . Measures like the COVID-19 lockdown will unlikely lead to step-changes in air quality. More comprehensive abatement measures are needed to control both primary pollutants and secondary  $\text{PM}_{2.5}$  and  $\text{O}_3$  in the future.

## Data Availability Statement

All code and data necessary for replication, including observed and meteorologically normalized air quality data, are openly available at Zenodo repositories (<http://doi.org/10.5281/zenodo.4620324>). Additional information about these data are available from the corresponding author upon reasonable request.

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## Erratum

In the originally published version of this article, Figure 2 and figures in the supporting information included city data for Taipei and Hong Kong. In keeping with the scope of the article, these data have been removed and the figures have been updated. The present version may be considered the authoritative version of record.