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Unsupervised PM$_{2.5}$ anomalies in China induced by the COVID-19 epidemic

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ABSTRACT

To stop the spread of COVID-19 (2019 novel coronavirus), China placed lockdown on social activities across China since mid-January 2020. The government actions significantly affected emissions of atmospheric pollutants and unintentionally created a nationwide emission reduction scenario. In order to assess the impacts of COVID-19 on fine particular matter (PM$_{2.5}$) levels, we developed a “conditional variational autoencoder” (CVAE) algorithm based on the deep learning to discern unsupervised PM$_{2.5}$ anomalies in Chinese cities during the COVID-19 epidemic. We show that the timeline of changes in number of cities with unsupervised PM$_{2.5}$ anomalies is consistent with the timeline of WHO's response to COVID-19. Using unsupervised PM$_{2.5}$ anomaly as a time node, we examine changes in PM$_{2.5}$ before and after the time node to assess the response of PM$_{2.5}$ to the COVID-19 lockdown. The rate of decrease of PM$_{2.5}$ around the time node in northern China is 3.5 times faster than southern China, and decreasing PM$_{2.5}$ levels in southern China is 3.5 times of that in northern China. Results were also compared with anomalous PM$_{2.5}$ occurring in Chinese’s Spring Festival from 2017 to 2019. PM$_{2.5}$ anomalies during around Chinese New Year in 2020 differs significantly from 2017 to 2019. We demonstrate that this method could be used to detect the response of air quality to sudden changes in social activities.

Keywords: COVID-19; PM$_{2.5}$; conditional variational autoencoder; emission reduction
1. INTRODUCTION

In recent years, China has committed to make every effort to improve air quality, which has led to significant improvements in air quality in the past years (Fan et al., 2020a; Zhang et al., 2020). PM$_{2.5}$ has been a major air quality concern across China, particularly in the wintertime owing to stronger precursor emissions associated with coal-fired heating and stable atmospheric boundary layers (Fan et al., 2020b). In addition, due to significant population migration and widespread firecracker use during the Chinese Lunar New Year, air quality worsens in this period (Yang et al., 2014). On December 31, 2019, the first case of novel coronavirus (COVID-19) pneumonia was reported in Wuhan in central China and then quickly spread to many other regions of China. To prevent the Chinese population from spreading COVID-19, the Chinese government announced and activated the First Level Response to Major Public Health Emergencies in Wuhan on January 23, 2020 (Sohrabi et al., 2020). Over the following two days, almost all other provinces and cities across China applied the same health response mechanism. Under this mechanism, individuals must isolate themselves at home and limit physical contact as much as possible. Accordingly, transportation services, entertainment venues, restaurants, and public gatherings were terminated or restricted (Tian et al., 2020; Chinazzi et al., 2020). As a result, after January 23, 2020, nationwide population migration in China plummeted following the COVID-19 lockdown and traffic volumes were considerably lower than those of the same period in previous years (Kraemer et al., 2020). Overall, the public health emergency greatly limited the activities of secondary and tertiary industries, and the number of people staying at home increase substantially (Chen et al., 2020). This lessened human activity can be expected to lead to marked declines in the emissions of primary air pollutants, thereby providing a unique scenario for examining air quality responses to air emissions.

Numerous studies conducted over the last several months have assessed air quality responses to nationwide emission reductions associated with the COVID-19 outbreak across
the globe. These studies investigate the relationship between COVID-19 mortality and peak concentrations of particulates (Setti et al., 2020) and associations between travel intensity; ambient concentrations of NO₂, PM₁₀, and PM₂.₅, and the number of confirmed cases of COVID-19 (Li et al., 2020). In general, such investigations from different countries and regions draw similar conclusions: limited social and industrial activities due to COVID-19 have significantly improved air quality levels (Kraemer et al., 2020; Freitas et al., 2020; Anjum et al., 2020; Grinberga-Zalite et al. 2021).

Given the country’s large land area and diverse ecosystems, climates, and industrial structures, it is almost impossible to implement a unified air emission control strategy across China. Further, as the First Level Response to Major Public Health Emergencies (FLRMPHE) came into effect just before the Chinese Lunar New Year and during the Spring Festival travel period, the public health event enables us to explore to what extent a sudden lockout and shut down of social and business activities may cause abnormal changes in air quality. We focus our assessment on PM₂.₅ (particle with an aerodynamic diameter of less than 2.5 μm), which is formed by its precursors released mostly through fossil fuel combustion and traffic emissions and is a priority air pollutant, particularly in the winter season. We sought to determine the timing at which abnormal changes in PM₂.₅ occurred after the COVID-19 outbreak to shed light on rapid air quality responses to emission abatement and help formulate air pollution control measures to be adopted in air pollution episodes.

Abnormal changes in ambient PM₂.₅ identified from its time series from a single air quality sampling station and from average regional mean PM₂.₅ concentrations across China are considered. As the FLRMPHE was activated across entire country, differences in economic and industrial structures, populations, personal incomes, and climates should result in considerable distinctions in PM₂.₅ responses to the COVID-19 lockdown in different cities and areas of China. In particular, when hourly, daily, weekly
(Gibergans-Baguena et al., 2020), and longer period changes in PM$_{2.5}$ induced by the COVID-19 lockdown are considered, it is not straightforward to simultaneously identify their respective abnormal changes. The anomaly of a time series is often defined by its departure from the mean or by a statistical error test. Using these classic concepts, one may find many anomalies in a time series that are not readily related to a significant social event such as the COVID-19 lockdown. To find the critical timing of PM$_{2.5}$ variations associated with the FLRMPHE and randomly identify a “true” (unsupervised) PM$_{2.5}$ anomaly for a certain period associated with the COVID-19 lockdown, we sought to simultaneously determine current site specific PM$_{2.5}$ anomalies across China based on historical ambient PM$_{2.5}$ concentrations and whether such abnormal changes in PM$_{2.5}$ are connected to the COVID-19 lockdown. To do so, we employ a variational autoencoder (VAE) to identify the occurrence of PM$_{2.5}$ anomalies at different time scales and in different cities. The VAE method is based on the deep learning method, which has been extensively applied in road traffic analyses and engineering in recent years (Xu et al., 2018; Boquet et al., 2020; An et al., 2015). Considering the aforementioned differences in emission sources, climates, and geographic conditions among different cities, we extend the VAE into a conditional variational autoencoder (CVAE) by using multiple cities as a VAE conditions to achieve simultaneous, unsupervised abnormal detection across different cities at different time scales (Chalapathy et al., 2019) and thus assess the nationwide impact of the COVID-19 outbreak on air quality. The development of the CVAE method based on deep learning is aimed to more realistically identify and assess anomalous and abrupt changes in PM$_{2.5}$, and to provide a new approach for source apportionment and detect the impact of meteorological conditions and human activities on significant anomalies of air pollutants and green house gases.

The CVAE method is presented in Section 2. Section 3 presents PM$_{2.5}$ anomaly detection results across Chinese cities, identify the differences of anomalous PM$_{2.5}$ events in different cities and regions in China occurring during the Chinese New Year from 2017 to
2020. Section 4 analyzes the primary factors contributing to abnormal PM$_{2.5}$ events, and Section 5 gives conclusions of the present study.

2. MATERIALS AND METHODS

2.1 Ambient PM$_{2.5}$ Concentrations

Hourly ambient mass concentrations of PM$_{2.5}$ were collected from the air monitoring data center of the Ministry of Ecology and Environment of the People's Republic of China (http://datacenter.mep.gov.cn). In total, 1436 monitor sites covering 354 cities and regions in China were set up since 2015 (Zhang et al., 2020). Given large uncertainties and the lack of quality control in measured PM$_{2.5}$ concentrations before 2017 (http://www.gov.cn/zhengce/2017-09/21/content_522663.htm), we only implemented hourly ambient PM$_{2.5}$ concentrations from 2017 to 2020 in our PM$_{2.5}$ anomaly analysis (Figure S1). These data were used to train the unsupervised PM$_{2.5}$ anomaly detection algorithm, i.e., the CVAE.

2.2 Concentration Anomaly Detection

Hourly and daily PM$_{2.5}$ concentrations fluctuate due to precursor emissions, weather conditions, and atmospheric chemistry. Thus, PM$_{2.5}$ always exhibits an “anomaly” from its mean. However, such anomaly cannot be used to identify significant concentration perturbation induced by a nationwide emergency like COVID-19. Given non-uniform distributions of PM$_{2.5}$ in different areas and at different times of a day, week, and month, to detect abnormal changes in PM$_{2.5}$, we developed an unsupervised anomaly detection method involving three components as shown in Figure 1: encoder, decoder, and anomaly evaluation. First, we trained the CVAE model, which is composed of an encoder and decoder. Historical hourly PM$_{2.5}$ concentration data from January 2017 to February 2020 (9721023 samples), were input into the CVAE as the training dataset. We used random sampling to extract 80% of the total samples to train the model and the remaining 20% of the PM$_{2.5}$
samples obtained from random sampling were used for model validation. We separated each sample based on 5 concentration features (moment, 3-hourly averaged, 8-hourly averaged, 12-hourly averaged, and daily (24-hour) averaged concentrations) and 6 time features (calendar year, calendar month, calendar week, calendar day, lunar month, and lunar day). These 11 features include both temporal and spatial information labeled by city names. The 354 cities were treated as conditions by the label encoder method and were input into the encoder and decoder. Briefly, in the CVAE model, we first mapped the input + conditions (PM$_{2.5}$ concentrations in our case) to the hidden space, mean, and variance by the encoder. We then estimated $z = \text{mean} + \text{variance} \times \epsilon$ [random sampling from the normal distribution $N(0, 1)$]. Finally, we used $z + \text{condition}$ as the input of the decoder to reconstruct the input, forming a structure from input to input. In other words, the structure first compresses the input data into the mean and variance and then reconstructs (restores) the input with the mean and variance. The encoder includes a hidden layer with 5 neurons that can convert the input data into their means and variances. Since the decoder and encoder are symmetrical, the decoder also includes a hidden layer with 5 neurons to reconstruct input data by means, variances and conditions. Due to the CVAE’s symmetry, inputs and outputs (reconstructed inputs) are the same during training process. A PM$_{2.5}$ anomaly occurs when abnormalities yield poorly reconstructed inputs of the CVAE and generate large errors. In unsupervised anomaly detection method, such error in the anomalies is set to be one order of magnitude larger than a mean error. An abnormal change in PM$_{2.5}$ is identified when the reconstruction error is 99%. The CVAE was adopted here to determine to what extent the change in PM$_{2.5}$ concentration could be set as a threshold to judge the occurrence of its concentration anomaly (Figure 1). For the sake of unintentional, we only use reconstructed PM$_{2.5}$ error to identify its anomalies but excluded the PM$_{2.5}$ anomaly due to the weekend effect which is subject to human interference. The present study focuses on daily variations in PM$_{2.5}$, which differ from city to city, rather than on long-term changes in PM$_{2.5}$, as long-term (e.g., weekly,
monthly, and seasonal) abnormal changes in PM$_{2.5}$ are often consistent over a large region. For example, after the nationwide COVID-19 lockdown, we observed an overall decline in PM$_{2.5}$ concentrations across northern China in February 2020. In fact, PM$_{2.5}$ concentrations continuously declined after the winter, which is not due to a public emergence event but the reduction of precursor emissions and favorable meteorological conditions.

3. RESULTS

3.1 PM$_{2.5}$ Concentration Anomaly Detection

We implemented the CVAE model trained by hourly PM$_{2.5}$ air concentrations in 354 cities in January and February from 2017 to 2020. Ambient PM$_{2.5}$ concentration anomalies for the 354 cities in China were detected in these two months from 2017 to 2020. Specific PM$_{2.5}$ concentration anomalies in each of 354 cities are provided in the Supplementary Data (https://github.com/yuanz18/pm2.5anomalies). The results reveal the occurrence of PM$_{2.5}$ anomalies among the Chinese cities during the New Year and Chinese Lunar New Year (or Spring Festival) periods (Supplementary Data). Figure 2 shows that PM$_{2.5}$ anomaly mainly occurs in the Spring Festival from 2017 to 2019. Interestingly, we observe a markedly different PM$_{2.5}$ anomaly trend during the 2020 Spring Festival in many cities from 2017 to 2019. The number of cities with anomalous PM$_{2.5}$ during the Spring Festival is significantly smaller than previous three years. This suggests that the lockdown likely reduced unsupervised PM$_{2.5}$ anomalies in many cities because this lockdown extended a long period after the Spring Festival in China. As a result, PM$_{2.5}$ concentrations did not bunch back or return to its normal status as the human and commercial activities did not resume after the holiday under the lockdown. We find that the period when PM$_{2.5}$ anomalies occurred in Chinese cities associated with COVID-19 is in line with the timeline of WHO (World Health Organization) response to COVID-19 (https://www.who.int/emergencies/diseases/novel-coronavirus-2019/interactive-timeline#!).
This timeline supersedes the WHO rolling updates and WHO timeline statement, which includes China’s lockdown activities and timelines.

To identify those cities without unsupervised anomalous PM$_{2.5}$ concentration in 2020, we estimated the difference of the number of cities with unsupervised anomalous PM$_{2.5}$ concentrations between 2020 and previous three years. The results reveal that 45 cities did not show unsupervised anomalous PM$_{2.5}$ concentration before and after the Spring Festival time node. By separating mainland China by a line that transects across China extending from Shanghai to the Tibetan border with India, we identify 44 cities to the north of this line (see Table S1 for details). As shown in Figure S2, the mean PM$_{2.5}$ level in these cities drop sharply between January and February in 2020.

As also shown in Figure 2, since the number of cities with anomalous PM$_{2.5}$ does not differ significantly from 2017 to 2019, we shall focus our PM$_{2.5}$ anomaly detection and comparison on 2019 and 2020. We calculated mean PM$_{2.5}$ levels collected from all selected cities averaged over January and February, and set this mean average PM$_{2.5}$ concentration as a reference baseline. As shown in Figure S3 and Figure S4, the baseline concentrations decreased 14.7 μg/m$^3$ in 2020 from 2019 whereas such difference between 2017 and 2018 was just 5.3 μg/m$^3$. Given that the CVAE identified the Spring Festival as a significant abnormal point (or time node), the changes in PM$_{2.5}$ concentrations before and after the Spring Festival are further compared (Figure S3-S6). As seen, PM$_{2.5}$ level declines after the 2020 Spring Festival and the degree of the decline (22.69 μg/m$^3$) is much greater than that in previous years. The lowest PM$_{2.5}$ baseline concentration (the green dashed line) from 2017 to 2020 and significant downward trend of PM$_{2.5}$ concentration after the Spring Festival in 2020 are observed (Figure S3), providing a special scenario subject to the COVID-19 lockdown.

Unsupervised PM$_{2.5}$ concentration anomalies derived by the CVAE occur during the Spring Festival from 2017 to 2020. The anomaly is likely associated with significantly
reduced human activities on the Chinese New Year’s Eve and widespread shooting off firecracker on the following day (namely, the Spring Festival), causing a remarkable increase in PM$_{2.5}$ concentrations. Given that the trend of anomalous PM$_{2.5}$ concentrations in those cities exhibit similar spatial-temporal distribution pattern, we shall focus our discussions on the PM$_{2.5}$ concentration differences before and after the Spring Festival as the time node in 2019 and 2020. Since the period with unsupervised abnormal changes in PM$_{2.5}$ during the Spring Festival holiday in 2020 overlaps with the COVID-19 lockdown, we refer this abnormal PM$_{2.5}$ event as the 2020 COVID-19 lockdown PM$_{2.5}$ anomaly episode in the subsequent discussion to distinguish it from the PM$_{2.5}$ anomaly occurring in 2019, which is referred to as the 2019 Lunar New Year PM$_{2.5}$ anomaly episode below.

3.2 Characteristics of Unsupervised Concentration Anomalies

As aforementioned, since the start of the 2020 COVID-19 lockdown PM$_{2.5}$ anomaly episode immediately follows the activation of the FLRMPHE on January 23, 2020, this anomaly is used as a key time node to elucidate characteristics of anomalous changes in PM$_{2.5}$ concentrations induced by the COVID-19 lockdown. As unsupervised PM$_{2.5}$ anomaly episode associated with the 2020 COVID-19 lockdown during the Spring Festival took place in 354 cities, we cannot present all these anomalies here but refer the readers to Supplementary Data. Instead, we estimate the fraction (percent change) in PM$_{2.5}$ concentrations for 354 cities based on the key time node defined by

$$c_f = \frac{\bar{C}_{\text{After node}}-\bar{C}_{\text{Before node}}}{\bar{C}_{\text{Before node}}} \times 100\%$$

where $\bar{C}_{\text{Before node}}$ and $\bar{C}_{\text{After node}}$ are hourly PM$_{2.5}$ concentrations before and after the time nodes from January to February, respectively. Figure 3 shows the spatial distribution of PM$_{2.5}$ fractions around the key time node associated with PM$_{2.5}$ concentration anomalies for 2019 and 2020. Known that February 3 in 2019 and January 23 in 2020 feature the onset of the Spring Festival travel rush, we set these two dates as key time nodes for PM$_{2.5}$ concentration anomalies subject to the 99% PM$_{2.5}$ reconstruction error for 2019 and 2020, respectively. The results show significant differences
between the concentration fractions for 2019 (Figure 3a) and 2020 (Figure 3b) and between northern and southern China.

For the 2019 Lunar New Year PM\textsubscript{2.5} anomaly episode, we observed positive PM\textsubscript{2.5} fractions in most cities in northern China, showing an increase in air concentrations after this PM\textsubscript{2.5} anomaly episode on February 3 during the Chinese Lunar New Year. During the 2020 COVID-19 lockdown PM\textsubscript{2.5} anomaly episode, concentrations show a significant decline, mostly in northern China. In fact, PM\textsubscript{2.5} levels in most cities decline after the 2020 COVID-19 lockdown PM\textsubscript{2.5} anomaly episode during the Spring Festival, but the extent of this decline in southern China in 2020 is less significant than that in 2019.

Cities with increasing PM\textsubscript{2.5} levels after the Chinese Lunar New Year are mostly located in the Yunnan and Guizhou provinces, which have some of the best air quality levels in China. While declines of PM\textsubscript{2.5} concentrations after the 2020 COVID-19 lockdown PM\textsubscript{2.5} anomaly episode is observed in many cities of northern China, PM\textsubscript{2.5} concentrations in Beijing increased markedly. Beijing ranked the sixth among the 8 cities, with PM\textsubscript{2.5} levels rising by 45.57\% after the COVID-19 lockdown PM\textsubscript{2.5} anomaly episode, whereas during the 2019 episode, PM\textsubscript{2.5} levels in Beijing decreased by 8.77\%. Several other cities positioned close to Beijing also show increases in PM\textsubscript{2.5} concentrations after the 2020 COVID-19 lockdown PM\textsubscript{2.5} anomaly episode, contrary to the expected decline in PM\textsubscript{2.5} levels due to the COVID-19 lockdown (Table S2). While major heavy industries in surrounding regions were not shut down with the onset of the COVID-19 epidemic, precursor emissions from these industries did not increase significantly. The observed trends may also be attributable to increasing household fossil fuel burning in neighboring provinces due to the significantly increased population returning home for the Lunar New Year holiday. The other causes of these rising PM\textsubscript{2.5} concentrations in Beijing and its surrounding areas have been assessed in several recent studies with regard to the COVID-19 lockdown effects on China’s air quality.
(Zhang et al., 2020; Dai et al., 2020; Le et al., 2020). This will be elaborated in Discussion section.

We further calculated differences in PM$_{2.5}$ fractions illustrated in **Figure 4** between 2019 and 2020, which were estimated by the fraction of the PM$_{2.5}$ anomaly of 2020 minus that of 2019. In northern China, PM$_{2.5}$ concentrations after the Lunar New Year anomaly episode of 2020 show a stronger decrease than those of the 2019 Lunar New Year episode. In **Figure 4**, the yellow solid line denotes a transect across China extending from Shanghai to the Tibetan border with India. Negative differences in PM$_{2.5}$ fractions are readily identified to the north of the transect line and positive differences in PM$_{2.5}$ fractions are found to the south, indicating stronger declines of PM$_{2.5}$ in northern China except in Beijing and its surroundings. Overall, the $c_f$ of 2020 is less than that of 2019 by -27.4% in northern China whereas the $c_f$ of 2020 is more than that of 2019 by 11.2% in southern China.

**Figure 5** shows unsupervised PM$_{2.5}$ concentration episode before and after the Chinese Lunar New Year occurring in southern and northern China from January 1st to the end of February in 2019 and 2020, respectively. Given that the 2020 Lunar New Year episode coincided with the COVID-19 lockdown, **Figure 5** also illustrates unsupervised anomalous changes in PM$_{2.5}$ occurring before and after the activation of the COVID-19 lockdown from January 1st to February 29, 2020. In northern China, PM$_{2.5}$ levels decline rapidly after the implementation of the COVID-19 lockdown. In 2019, PM$_{2.5}$ concentrations show no marked decline in northern China after the Chinese Lunar New Year’s anomalous episode. In southern China, PM$_{2.5}$ concentrations exhibit no significant changes before and after the onset of the COVID-19 lockdown in 2020 but clearly decline in 2019 than that in 2020. The mean PM$_{2.5}$ concentration averaged over January and February in southern China decreases by 6.87 $\mu$g/m$^3$ from 2019 to 2020 or by 16.3% of the mean concentration in 2019 (**Table S3**). This likely heavily affected the changes in PM$_{2.5}$ before and after the 2020 COVID-19 lockdown PM$_{2.5}$ anomaly episode. The observed lack of significant declines in PM$_{2.5}$
concentrations in 2020 in many cities of southern China might also be attributed to relatively lower PM$_{2.5}$ concentrations and precursor emissions (e.g., from domestic heating), which yielded weak anomalous changes in PM$_{2.5}$ concentrations (Dai et al., 2020; Le et al., 2020). In northern China, the difference between 2020 and 2019 was measured at 3.2 µg/m$^3$, accounting for 4.58% of the mean PM$_{2.5}$ concentration averaged over January and February. Nationwide PM$_{2.5}$ concentrations dropped by 4.7 µg/m$^3$, accounting for 8.03% of the mean concentration averaged over January and February 2019 and the mean concentration in northern China is higher than that in southern China (Table S4).

4. DISCUSSIONS

An anomaly detection method for PM$_{2.5}$ based on CVAE deep learning was developed to discern unsupervised PM$_{2.5}$ anomalies extracted from complex variations in PM$_{2.5}$ concentrations. We examined unsupervised PM$_{2.5}$ anomalies mainly occurring during the China’s Spring Festival from 2017 to 2020. The CVAE model reveals markedly smaller number of cities with anomalous PM$_{2.5}$ in northern China in 2020 than that from 2017 to 2019 (Figure 2). The changes in the number of cities responding to COVID-19 lockdown featured by anomalous PM$_{2.5}$ agree nicely with the timeline of WHO’s response to COVID-19. The observed unsupervised abnormal PM$_{2.5}$ concentrations reflect strong fluctuations due to human activities and holiday effects. The unsupervised anomalies occurred almost simultaneously in most cities across China (Supplementary Data). Even though the Chinese New Year related PM$_{2.5}$ anomalies started on Lunar New Year’s Eve and were associated with the holiday effect, the 2020 COVID-19 lockdown PM$_{2.5}$ anomaly episode displays unique characteristics. From January 23 to 25, the provincial governments of China successively adopted the First Level Public Health Emergency Response (Table S5), terminating population migration and group business activities in China. The FLRMPHE has been extended to 3-4 months in different provinces and megacities. The China Energy Administration reports that the power consumption in January and February
2020 fell by 7.8% relative to the same period in 2019, secondary industry power consumption fell by 12%, but residential electricity consumption increased by 2.4% (http://www.nea.gov.cn/2020-03/20/c_138898634.htm). Road freight volumes for January and February 2020 were 79.4% and 72.4% of that in the same period in 2019, and the volumes of road passenger transportation in January and February 2020 were merely 88.8% and 47% of those of the same period in 2019 (http://www.mot.gov.cn/tongjishuju/gonglu/).

These substantially reduced social and industrial activities likely reduced primary emissions of air pollutants (Huang et al., 2020; Angelevska et al., 2021). A comparison between the 2019 Lunar New Year PM$_{2.5}$ anomaly episode and 2020 COVID-19 lockdown PM$_{2.5}$ anomaly episode occurring on Chinese Lunar New Year’s Eve and New Year’s Day shows distinct responses to social and business activities. In the 2020 COVID-19 lockdown PM$_{2.5}$ anomaly episode, however, because the FLRMPHE was extended to 3-4 months in different provinces, no increase social activity occurred. As a result, unsupervised PM$_{2.5}$ anomalies become weakly altered after Lunar New Year’s Day at a relatively low level, suggesting that PM$_{2.5}$ concentrations were not strongly affected anymore. Figure S7 shows measured mean daily air concentrations of PM$_{2.5}$, nitrogen dioxide (NO$_2$), and sulfur dioxide (SO$_2$) averaged over China for January and February of 2019 and 2020. In general, NO$_2$ and SO$_2$ exhibit similar fluctuations and trends to those of PM$_{2.5}$, suggesting that precursor emissions contributed to PM$_{2.5}$ variations. For 2019, we identify declining concentrations of PM$_{2.5}$, NO$_2$, and SO$_2$ until Lunar New Year’s Eve and subsequent increases. In 2020, however, levels of these air pollutants continuously decrease from Lunar New Year’s Day (January 25, 2020) onward, again due to the stagnation of social and business activities under the FLRMPHE. It should be noted that many factors such as meteorology, precursor emissions, and atmospheric chemistry could contribute to significant anomalies of an air pollutant. Anomaly of a time series of air pollutants is often simply estimated as the departure from the mean of the time series. The anomaly obtained by this method could be easily manipulated
by the duration of the time series and site dependent, and sometimes misleading, causing uncertainties in emission reduction decisions. As aforementioned, the strength of CVAE anomaly detection in our case lies in objective detection of abnormal events of air pollution and automatic warning of abrupt changes in air pollution, thereby providing more reliable results to policy makers for air emission reduction. Zhong et al. (2018) have examined the effect of emission and meteorological factors on PM$_{2.5}$ fluctuations in China. Their results revealed that precursor emissions overwhelmed meteorological factors, particularly in eastern and central China where most unsupervised PM$_{2.5}$ anomalies were observed. Figure S8 shows the anomalies of the two-month mean surface pressure and temperature averaged over January and February 2019 and 2020 across China, respectively, calculated as the departure from their two-month means over 1981 to 2020. The positive pressure anomalies and negative temperature anomalies in 2019 can be identified in eastern and central China whereas in 2020 opposite anomalies are observed. The results indicate a warmer January and February in 2020 than 2019. Since PM$_{2.5}$ concentrations in eastern China are positively correlated with the air temperature and negatively correlated with surface pressure (Zhong et al., 2018), we would expect the decrease in two-monthly mean PM$_{2.5}$ concentrations in 2020 than that in 2019. However, the measurement results revealed lower concentrations in 2020 as compared with that in 2019 (Figures S1, baseline concentrations in Figures S3-S6, and S7). This suggests that the meteorological factors played a less significant role from a national perspective as compared to precursor emissions, in line with Zhong et al (2018)’s findings. Differing from most cities with low PM$_{2.5}$ contamination right after the COVID-19 lockdown, PM$_{2.5}$ levels increased in Beijing during the lockdown (Figure 3). This exception has been intensively investigated by Le et al. (2020). Their findings indicated that the increase of PM$_{2.5}$ concentrations in Beijing was mainly attributed to poor diffusion conditions due to very weak wind speed, increase in relative humidity, and the decline of the atmospheric boundary layer height in this metropolitan city and the Northern China Plane.
In this case, the meteorological factors played an important role in this heavy PM$_{2.5}$ pollution event during the COVID-19 lockdown.

Overall, from the COVID-19 lockdown, Our CVAE anomaly detection suggest that the number of cities with declining PM$_{2.5}$ levels increased from 281 in 2019 to 314 in 2020, and the rate of decline also increased from 25% to 71.3%, suggesting stronger precursor emission reductions of PM$_{2.5}$ in 2020 episode (Zhang et al., 2015). He et al. (2020) suggested that the impact of lockdown was stronger in northern Chinese cities than southern China, consistent with our CVAE anomaly detection result, showing that decreasing PM$_{2.5}$ levels around the anomaly time node in northern China was 32.71 μg/m$^3$, higher than decreasing PM$_{2.5}$ level at 9.23 μg/m$^3$ in southern China, though PM$_{2.5}$ levels in locked-down cities were still significantly higher than China’s ambient air quality standard (35 μg/m$^3$) (http://106.37.208.228:8082/). These results confirm that the effects of COVID-19 lockdown on air pollution in Chinese cities are associated with local economy, industrial, and social activities. After returning normal life, the improvement in air quality induced by control measures during the lockdown would be, to some extent, offset in a longer term. However, the assessment of abrupt and unprecedented changes in PM$_{2.5}$ presented in our study may provide valuable policy lessons for air emission mitigations.

5. Conclusions

China has adopted local and regional air emission control strategies to guarantee the success of important national and international events in China, including the G20 summit held in Hangzhou, the capital city of Zhejiang province, in 2016 (Feng et al., 2019; Ji et al., 2018). Given varying meteorological conditions, geometries, primary emission sources (Huang et al., 2014), atmospheric transport pathways, and chemical compositions (Geng et al., 2017), emission control measures adopted in one region might not be applicable to another region. The COVID-19 lockdown provides a unique opportunity to examine air
quality responses to primary emissions induced by social and industrial activities at the local, regional, and national scales. The present study employed the CVAE derived by deep learning to identify the potentially most sensitive PM$_{2.5}$ anomaly period as a reflection of air quality responses to a significant public health emergency. Understanding and quantifying such a response could help us quickly identify key processes that shape abnormal changes in PM$_{2.5}$ and to what extent significant social and business activities may otherwise cause changes in air emissions and contamination levels.

ASSOCIATED CONTENT

Supporting Information
The Supporting Information and Data are available free of charge on the Elsevier Publications website, including: 45 anomaly cities; ratio of PM$_{2.5}$ changes in 8 cities; change of PM$_{2.5}$ level in southern and northern China; PM$_{2.5}$ level around anomaly; date of FLPHER in different area; PM$_{2.5}$ concentration change from 2015 to 2020; PM$_{2.5}$ level in the south and north of the transect line; PM$_{2.5}$ level around Chinese New Year; plot of concentration for PM$_{2.5}$, NO$_2$ and SO$_2$; surface pressure and air temperature averaged over January and February.

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Notes
The authors declare no competing financial interest.

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REFERENCES

An, J., Cho, S., 2015. Variational Autoencoder Based Anomaly Detection Using Reconstruction Probability.
Angelevska, B., Atanasova, V., Andreevski, I., 2021. Urban Air Quality Guidance Based on Measures Categorization in Road Transport. Civil Engineering Journal 7, 253–267. https://doi.org/10.28991/cej-2021-03091651
Anjum, N. A., 2020. Good in The Worst: COVID-19 Restrictions and Ease in Global Air Pollution. https://doi.org/10.20944/preprints202004.0069.v1.
Boquet, G., Morell, A., Serrano, J., Vicario, J. L., 2020. A Variational Autoencoder Solution for Road Traffic Forecasting Systems: Missing Data Imputation, Dimension Reduction,
Model Selection and Anomaly Detection. Transp. Res. Part C Emerg. Technol. 115, 102622. https://doi.org/10.1016/j.trc.2020.102622.

Chalapathy, R., Chawla, S., 2019. Deep Learning for Anomaly Detection: A Survey. ArXiv190103407 Cs Stat.

Chen, K., Wang, M., Huang, C., Kinney, P. L., Paul, A. T., 2020. Air Pollution Reduction and Mortality Benefit during the COVID-19 Outbreak in China. medRxiv. 2020.03.23.20039842. https://doi.org/10.1101/2020.03.23.20039842.

Chinazzi, M., Davis, J. T., Ajelli, M., Gioannini, C., Litvinova, M., Merler, S., Piontti, A. P., Mu, K., Rossi, L., Sun, K., 2020. The Effect of Travel Restrictions on the Spread of the 2019 Novel Coronavirus (COVID-19) Outbreak. Science. 368 (6489), 395–400. https://doi.org/10.1126/science.aba9757.

Dai, Q., Liu, B., Bi, X., Wu, J., Liang, D., Zhang, Y., Feng, Y., Hopke, P. K., 2020. Dispersion Normalized PMF Provides Insights into the Significant Changes in Source Contributions to PM$_{2.5}$ after the COVID-19 Outbreak. Environ. Sci. Technol. 54 (16), 9917–9927. https://doi.org/10.1021/acs.est.0c02776.

Fan, H., Zhao, C., Yang, Y., 2020a. A Comprehensive Analysis of the Spatio-Temporal Variation of Urban Air Pollution in China during 2014–2018. Atmos. Environ. 220, 117066. https://doi.org/10.1016/j.atmosenv.2019.117066.

Fan, M., He, G., Zhou, M., 2020b. The Winter Choke: Coal-Fired Heating, Air Pollution, and Mortality in China. J. Health Econ. 71, 102316. https://doi.org/10.1016/j.jhealeco.2020.102316.

Feng, R., Wang, Q., Huang, C., Liang, J., Luo, K., Fan, J., Cen, K., 2019. Investigation on Air Pollution Control Strategy in Hangzhou for Post-G20/Pre-Asian-Games Period (2018–2020). Atmospheric Pollut. Res. 10 (1), 197–208. https://doi.org/10.1016/j.apr.2018.07.006.

Freitas, E. D., Ibarra-Espinosa, S. A., Gavidia-Calderón, M. E., Rehbein, A., Rafee, S. A. A., Martins, J. A., Martins, L. D., Santos, U. P., Ning, M. F., Andrade, M. F., 2020. Mobility Restrictions and Air Quality under COVID-19 Pandemic in São Paulo, Brazil. https://doi.org/10.20944/preprints202004.0515.v1.

Geng, G., Zhang, Q., Tong, D., Li, M., Zheng, Y., Wang, S., He, K., 2017. Chemical Composition of Ambient PM$_{2.5}$ over China and Relationship to Precursor Emissions during 2005–2012. Atmospheric Chem. Phys. 17 (14), 9187–9203. https://doi.org/10.5194/acp-17-9187-2017
Gibergans-Baguena, J., Hervada-Sala, C., Jarauta-Bragulat, E., 2020. The Quality of Urban Air in Barcelona: A New Approach Applying Compositional Data Analysis Methods. Emerging Science Journal 4, 113–121. https://doi.org/10.28991/esj-2020-01215

Grinberga-Zalite, G., Pilvere, I., Muska, A., Kruzemtra, Z., 2021. Resilience of Meat Supply Chains during and after COVID-19 Crisis. Emerging Science Journal 5, 57–66. https://doi.org/10.28991/esj-2021-01257

He, G., Pan, Y., Tanaka, T., 2020. The short-term impacts of COVID-19 lockdown on urban air pollution in China. Nature Sustainability, 3, 1005–1011. https://doi.org/10.1038/s41893-020-0581-y.

Huang, R.J., Zhang, Y., Bozzetti, C., Ho, K.F., Cao, J.-J., Han, Y., Daellenbach, K. R., Slowik, J. G., Platt, S. M., Canonaco, F., 2014. High Secondary Aerosol Contribution to Particulate Pollution during Haze Events in China. Nature. 514 (7521), 218–222. https://doi.org/10.1038/nature13774.

Huang, X., Ding, A., Gao, J., Zheng, B., Zhou, D., Qi, X., Tang, R., Ren, C., Nie, W., Chi, X., Wang, J., Xu, Z., Chen, L., Li, Y., Che, F., Fang, N., Wang, H., Tong, D., Qin, W., Cheng, W., Liu, W., Fu, Q., Chai, F., Dai, G. J., Zhang, Q., He, K., 2020. Enhanced secondary pollution offset reduction of primary emissions during COVID-19 lockdown in China. eartharxiv.org/hvuzy.

Ji, Y., Qin, X., Wang, B., Xu, J., Shen, J., Chen, J., Huang, K., Deng, C., Yan, R., Xu, K., 2018. Counteractive Effects of Regional Transport and Emission Control on the Formation of Fine Particles: A Case Study during the Hangzhou G20 Summit. Atmospheric Chem. Phys. 18 (18), 13581–13600. https://doi.org/10.5194/acp-18-13581-2018.

Kraemer, M. U. G., Yang, C.-H., Gutierrez, B., Wu, C.-H., Klein, B., Pigott, D. M., Group, open C.-19 data working., Plessis, L. du., Faria, N. R., Li, R., 2020. The Effect of Human Mobility and Control Measures on the COVID-19 Epidemic in China. medRxiv. 2020.03.02.20026708. https://doi.org/10.1101/2020.03.02.20026708.

Le, T., Wang, Y., Liu, L., Yang, J., Yung, Y. L., Li, G., Seinfeld, J. H., 2020. Unexpected Air Pollution with Marked Emission Reductions during the COVID-19 Outbreak in China. Science, 369 (6504), 702–706. https://doi.org/10.1126/science.abb7431.

Li, W., Chen, X., 2020. The Nexus of Travel Restriction, Air Pollution and COVID-19 Infection: Investigation from a Megacity of the Southern China. medRxiv. 2020.04.25.20079335. https://doi.org/10.1101/2020.04.25.20079335.

Setti, L., Passarini, F., Gennaro, G. D., Barbieri, P., Perrone, M. G., Piazzalunga, A., Borelli, M., Palmisani, J., Gilio, A. D., Piscitelli, P., 2020. The Potential Role of Particulate
Matter in the Spreading of COVID-19 in Northern Italy: First Evidence-Based Research Hypotheses.

medRxiv. 2020.04.11.20061713. https://doi.org/10.1101/2020.04.11.20061713.

Sohrabi, C., Alsafi, Z., O’Neill, N., Khan, M., Kerwan, A., Al-Jabir, A., Iosifidis, C., Agha, R., 2020. World Health Organization Declares Global Emergency: A Review of the 2019 Novel Coronavirus (COVID-19). Int. J. Surg. 76, 71–76. https://doi.org/10.1016/j.ijsu.2020.02.034.

Tian, H., Liu, Y., Li, Y., Wu, C.-H., Chen, B., Kraemer, M. U. G., Li, B., Cai, J., Xu, B., Yang, Q., 2020. An Investigation of Transmission Control Measures during the First 50 Days of the COVID-19 Epidemic in China. Science. 368 (6491), 638–642. https://doi.org/10.1126/science.abb6105.

Xu, H., Chen, W., Zhao, N., Li, Z., Bu, J., Li, Z., Liu, Y., Zhao, Y., Pei, D., Feng, Y., 2018. Unsupervised Anomaly Detection via Variational Auto-Encoder for Seasonal KPIs in Web Applications. Proc. World Wide Web Conf. World Wide Web - WWW 18 2018, 187–196. https://doi.org/10.1145/3178876.3185925.

Yang, L., Gao, X., Wang, X., Nie, W., Wang, J., Gao, R., Xu, P., Shou, Y., Zhang, Q., Wang, W., 2014. Impacts of Firecracker Burning on Aerosol Chemical Characteristics and Human Health Risk Levels during the Chinese New Year Celebration in Jinan, China. Sci. Total Environ. 476–477, 57–54. https://doi.org/10.1016/j.scitotenv.2013.12.110.

Zhang, L., Yang, G., Li, X., 2020. Mining Sequential Patterns of PM2.5 Pollution between 338 Cities in China. J. Environ. Manage. 262, 110341. https://doi.org/10.1016/j.jenvman.2020.110341.

Zhong, Q., Ma, J., Shen, G., Shen, H., Zhu, X., Yun, X., Meng, W., Cheng, H., Liu, J., Li, B., Wang, X., Zeng, E. Y., Guan, D., Tao, S., 2018. Distinguishing Emission-Associated Ambient Air PM2.5 Concentrations and Meteorological Factor-Induced Fluctuations. Environ. Sci. Technol. 52 (18), 10416–10425. https://doi.org/10.1021/acs.est.8b02685.

Zhang, Q., Shen, Z., Cao, J., Zhang, R., Zhang, L., Huang, R.-J., Zheng, C., Wang, L., Liu, S., Xu, H., 2015. Variations in PM2.5, TSP, BC, and Trace Gases (NO2, SO2, and O3) between Haze and Non-Haze Episodes in Winter over Xi’an, China. Atmos. Environ. 112, 64–71. https://doi.org/10.1016/j.atmosenv.2015.04.033.

Zhang, R., Zhang, Y., Lin, H., Feng, X., Fu, T. M., Wang, Y., 2020. NOx Emission Reduction and Recovery during COVID-19 in East China. Atmosphere, 11 (4), 433. https://doi.org/10.3390/atmos11040433.
Figure captions

Figure 1. CVAE flow chart for PM$_{2.5}$ anomaly detection. From left to right, the system includes two subsystems (features): the PM$_{2.5}$ concentration processing subsystem (feature) shown in green and the date subsystem (feature) shown in blue as the input ($x$) of the encoder. First, the encoder converts $x$ into $u$ (mean) and $\sigma$ (variance). Then, decoder inputs latent variable $z$ and generates $\hat{x}$. If the output error is more than 99% of the reconstruction error, an anomalous change in PM$_{2.5}$ occurs.

Figure 2. Number of cities with anomalous PM$_{2.5}$ in January and February from 2017 to 2020 (a-d). The purple circles in Fig. 2d represent the timeline of WHO’s response to COVID-19.

Figure 3. Fractions of PM$_{2.5}$ concentrations for 2019 (a) and 2020 (b) based on PM$_{2.5}$ anomalies occurring during Chinese Lunar New Year holiday in 354 cities based on the time nodes in February 3, 2019 (33 days before and 26 days after the Spring Festival) and January 23 in 2020 (22 days before and 38 days after the Spring Festival), respectively.

Figure 4. PM$_{2.5}$ changes in southern and northern China based on $c_f$ in 2019 and 2020. Yellow solid line denotes a transect across China extending from Shanghai to the Tibetan border with India.

Figure 5. Distribution, median (white solid line), and quantile for 25% to 75% (white dashed line) of PM$_{2.5}$ concentrations before (red) and after (blue) the anomalies node in 2019 and 2020 in southern (left panel) and northern (right panel) China. The nodes are February 3 in 2019 (33 days before and 26 after the Spring Festival) and January 23 in 2020 (22 days before and 38 days after the Spring Festival), respectively.
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Graphical abstract
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Declaration of Interests

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.
Highlights
- CVAE anomaly detection is developed to discern abrupt changes in PM$_{2.5}$
- The timeline of PM$_{2.5}$ anomalies is consistent with WHO's response to COVID-19
- PM2.5 anomalies during Chinese New Year in 2020 differs from 2017 to 2019
- Rate of PM2.5 decline during Chinese New Year is faster in northern China