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Short-term air pollution exposure and COVID-19 infection in the United States☆

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ABSTRACT

The Sars-CoV-2 disease (known as COVID-19) has become a global public health emergency. Researchers have been unveiling the transmission mechanisms and disclosing possible contributing factors. Studies have theorized plausible linkage mechanisms between air pollution exposure and COVID-19 infection and have divided the air pollution exposure into two types: long-term exposure and short-term exposure. However, present studies on impacts of short-term exposure have not reached a conclusive result and are mostly focusing on Asian and European countries. In this study, we conduct a nationwide analysis to examine the association between short-term air pollution exposure and COVID-19 infection in the United States. Daily confirmed cases, air pollution information, and meteorological factors at the county level were collected between March 1st and June 30th, 2020. A total of 806 (out of 3143) counties were included in this study, with 554 counties for $PM_{2.5}$ and 670 counties for ozone (O_3), which account for around 2.1 million cumulative confirmed cases, i.e., about 80% of all confirmed cases in the U.S. over the study period. A generalized additive model was applied to investigate the relationship between short-term exposure to $PM_{2.5}/O_3$ and COVID-19 confirmed cases. The statistically significant results indicate that, with every 10 $\mu g/m^3$ increase in mean pollutant concentration, the number of daily confirmed cases increases by 9.41% (CI: 8.77%–10.04%) for $PM_{2.5}$ and by 2.42% (CI: 1.56%–3.28%) for O_3. The relative risks associated with short-term $PM_{2.5}$ exposure remain positive after isolating the impacts of long-term exposure. The results of this study suggest that short-term exposure to air pollution, especially to $PM_{2.5}$, may contribute to the spread and course of the pandemic. This finding has important implications for policymakers and the public to take preventive measures such as staying at home on polluted days while improving ventilation indoors to lower the probability of infection.

1. Introduction

Coronavirus disease (COVID-19), caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), has swept the world as a pandemic. As of July 30th, 2021, there have been over 196 million confirmed cases and over 4.2 million deaths globally (WHO, 2021). Air transmission has been recognized as a primary way for the virus to spread (The Lancet Respiratory Medicine, 2020). Environmental factors have long been recognized as potential contributors to virus transmission, such as in the case of influenza (Liang et al., 2014), SARS (Cui et al., 2003), and dengue (Liu et al., 2020). Air pollution, which has shown strong association with increasing incidence of respiratory and cardiovascular diseases (Hoek et al., 2013; Lee et al., 2014), presents the potential of escalating risk for infection. However, air pollution exposure association with increased COVID-19 infection remains largely unknown (Daraei et al., 2020; Mehmood et al., 2020).

Based on the transmission and infection mechanism of COVID-19, Isphording and Pestel (2021) summarized three plausible linkages between air pollution and the spread and course of COVID-19. First, long-term air pollution exposure leads to certain medical preconditions of susceptible groups. Second, short-term exposure can induce acute respiratory inflammation and lower people's immune responses to new infections (Tung et al., 2021). Lastly, suspending aerosols and particulate matter (PM) could prolong the duration of the virus remaining in the air to increase the chance of airborne infection (Morawska and Milton, 2020). Fine particulate matter and O_3 are the two pollutants of major concern. Particulate matter was found

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to increase the expression of angiotensin-converting enzyme 2 (ACE2) in lungs, which provides the main adhesion and entrance for SARS-CoV-2 (Hoffmann et al., 2020; Tung et al., 2021). It was found that by penetrating deeply into the lung, $PM_{10}/PM_{2.5}$, whose aerodynamic diameter is no more than 10 or 2.5 μm, can cause respiratory tract inflammation and paralyze the cilium airway. In addition, the virus can possibly stay viable for hours by adhering to PM. Then, due to its small diameter, inhaled virus-laden PM can directly transport the virus deep into alveolar and tracheobronchial regions (Qu et al., 2020).

Another major pollutant that can stimulate the respiratory system and decrease pulmonary functionality is O_3. Exposure to O_3 has been found to be closely related to immune-inflammation and permeability (Cabello et al., 2015; Nuvolone et al., 2018), injury of the respiratory system (Michaudel et al., 2018, 2016; Zhang et al., 2019) and systemic systems (Daraei et al., 2020) which increases the risk of developing COVID-19. It was suggested that short-term exposure tends to promote inflammation while long-term exposure can lead to immune dysregulation and other medical conditions (Wang et al., 2020a). Despite diverse theories about the linking mechanisms between air pollution exposure and COVID-19 prevalence (Contini and Costabile, 2020; Daraei et al., 2020; Frontera et al., 2020; Mehmood et al., 2020; Morawska and Milton, 2020; Tung et al., 2021), quantitative studies are needed to assess and validate those conjectures.

Researchers have investigated both long-term and short-term air pollution exposure association with COVID-19 prevalence and mortality. Typically, long-term exposure refers to exposure to air pollution for years before the onset of the disease, while short-term exposure refers to exposure that occurs during the duration of a pandemic. Pansini and Fornacca (2021) have found significantly positive correlation between long-term air pollution exposure to COVID-19 infection across 8 nations. Wu et al. (2020) conducted a study within the U.S. context using a multivariate regression model finding that long-term exposure to $PM_{2.5}$ was positively associated with COVID-19 mortality.

As for the effects of short-term exposure, several statistical analyses have concentrated on Europe and Asia, mostly relying on time series analysis. Several studies in China have found positive correlation between short-term exposure and confirmed cases (Li et al., 2020; Xie and Zhu, 2020; Zhang et al., 2021). A study in Japan found short-term exposure to suspended particle matter (SPM) rather than $PM_{2.5}$, NO_x, and O_x was positively related to confirmed cases (Azuma et al., 2020). Isphording and Pestel (2021) carried out a time series analysis across German cities and found that the number of daily new cases was positively correlated with short-term concentration of PM_{10} but not O_3. Despite these findings in Europe and Asia, little is known about the short-term exposure impacts on COVID-19 infection in the United States. A case study in California, found that COVID-19 confirmed cases and deaths were significantly correlated with the daily mean concentrations of $PM_{2.5}$, PM_{10}, SO_2, and NO_2 (Bashir et al., 2020). Another study found positive association between short-term O_3 exposure and COVID-19 cases in Queens, New York (Adhikari and Yin, 2020). Still, studies at the national scale in the U.S. are lacking. Therefore, the objective of this study is to investigate the nationwide impacts of short-term air pollution exposure to COVID-19 infection in U.S counties. $PM_{2.5}$ and O_3 are selected as the focus pollutants since they are the most dominant pollutants in the U.S.

2. Methodology

2.1. Data collection

Daily confirmed cases for each county between March 1st, 2020 and June 30th, 2020 were retrieved from the COVID-19 data repository at Johns Hopkins University (Dong et al., 2020). COVID-19 infection refers to the confirmed cases in this study. The start date was set as March 1st since the pandemic started to ramp up in March in the U.S. County-level air quality data were collected from the website of the U.S. Environmental Protection Agency (EPA), containing the daily measured Air Quality Index (AQI) information per pollutant of every county (U.S. Environmental Protection Agency, 2020a). The AQI value represents the level of severity for air pollution. The daily AQI value for each individual pollutant is calculated based on the corresponding concentration as regulated by EPA (U.S. Environmental Protection Agency, 2018). Since AQI is restricted within the U.S. context, after obtaining the daily AQI values of each pollutant, the daily concentration (in $\mu g/m^3$ units) of corresponding pollutants, which is more universally understandable, was reversely deducted.

Meteorological information including daily mean temperature, dew point, and wind speed was mainly obtained from the website of the National Centers for Environmental Information, which provides open access to archives for environmental data collected by meteorological stations (National Oceanic and Atmospheric Administration, 2020). The county-level meteorological information was gathered by matching the nearest weather station to the center of each county. There are 2705 stations in the U.S. with monitoring data during our study period, which adequately covers our study area. Since the coverage area and corresponding population data of each station is not accessible, we chose to use the weather station closest to the county center rather than average the parameters from all stations in the same county. In this study, relative humidity (RH, %), calculated from mean temperature and dew point, was used to better represent the impacts of humidity and for more intuitive interpretation than dew point. For counties with missing data percentages ranging between 10% and 25% (12 counties)—mostly due to monitoring issues—missing data were imputed by replacing the missing values with historical data of a nearest station from the Weather Underground (Weather Underground, 2021). Weather Underground provides historical data collected by three major sources: Automated Surface Observation System (ASOS), Personal Weather Stations (PWS), and National Oceanic and Atmospheric Administration (NOAA), which can act as a supplementary data source to impute the missing data. Counties with more than 25% missing data were removed from future analysis.

2.2. Study area

After merging the above-mentioned datasets, counties without comprehensive information (i.e., missing meteorological data, or both type of air pollutants data) or no confirmed cases within the study period were excluded from further analysis. The geographical distribution of counties with $PM_{2.5}$ and O_3 data is provided in Fig. 1. As evident in the figure, the study area covers most of the metropolitan areas in the U.S.

2.3. Statistical analysis

This study examined the association between short-term air pollution exposure and COVID-19 infection in the U.S. by using a generalized additive model (GAM). It is a form of generalized linear model in which the linear predictor is replaced by a user specified sum of smooth functions, which has been widely used in time series analysis investigating the relationship between environmental factors and health outcomes (Liu et al., 2020; Ma et al., 2020; Samet et al., 2000). The model is formulated as:

$$Log\left(case_{i,t}\right) = \beta_0 + \beta_1 \cdot \overline{Cpoll}_{i,lag(l)} + s(temp, 3) + s(RH, 3) + s(wind, 3) + county_i + date_t + DOW + Log\left(case_{i,t-1}\right) + \varepsilon_{i,t} \quad (1)$$

where.

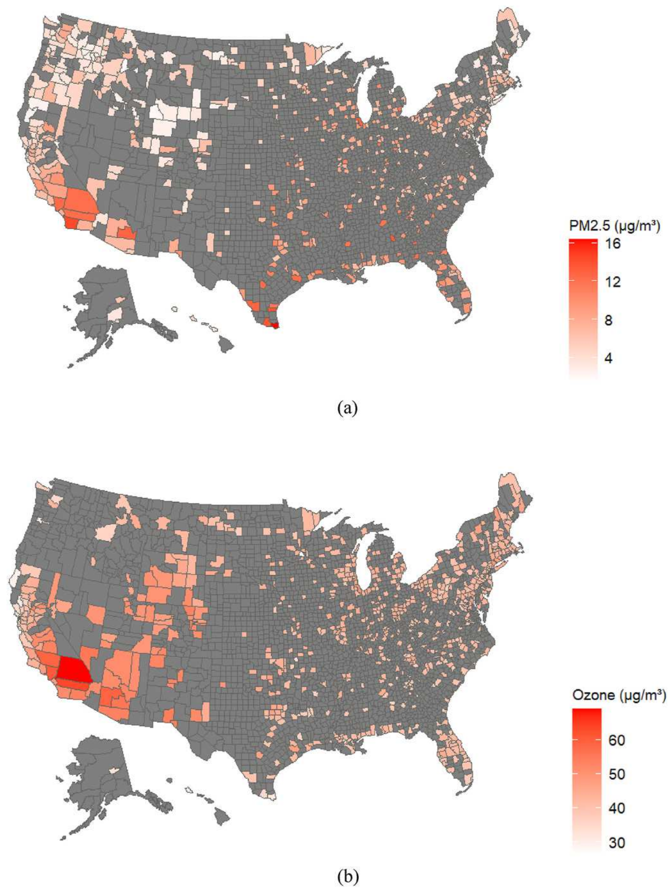


Fig. 1. Counties with (a) $PM_{2.5}$ data and (b) O_3 data and corresponding mean concentration (highlighted in red). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

$case_{i,t}$ is the daily confirmed new cases for county i on date t.

$\overline{Cpoll}_{i,lag(l)}$ is the moving average (*lag*) concentration (in $\mu g/\ m^3$ units) of selected pollutants over l days in county i,

temp is daily mean temperature (°C).

RH is daily relative humidity (%).

wind is mean wind speed (m/s).

$s(\cdot)$ is smooth function with maximal 3 degrees of freedom.

$county_i$ is a dummy variable representing each county i,

$date_t$ is the date for each day during the study period.

DOW is day of week, coded as dummy variables.

The dependent variable is $case_{i,t}$, whose link function is a log transformation assuming a Poisson distribution. The focus independent variable is $\overline{Cpoll}_{i,lag(l)}$. The time lag value ranges from 1 to 14 since the median incubation period of the disease is 5.1 days and most people (99%) will develop symptoms within 14 days of infection (Lauer et al., 2020). Meteorological parameters including mean temperature, relative humidity, and wind speed, were selected due to potential impacts demonstrated by previous studies (Azuma et al., 2020; Xie and Zhu, 2020). In addition, the fixed effects of each county ($county_i$) and day ($date_t$) during the study period are incorporated into the model to represent the differences in responses to the pandemic across counties over the study period. The dummy variable $county_i$ controls for county-level time-invariant characteristics (e.g., economic activities, population density). $Log(case_{i,t-1})$ is the log transformation of confirmed cases for the previous day, which is included into the model to account for possible serial correlation of the time series data. The *Relative Risk (RR)* and corresponding 95% confidence interval (*CI*) are reported as the results for every 10 $\mu g/m^3$ increase for concentration of selected pollutants. The two metrics are calculated as follows:

$$Relative\ Risk\ (RR) = [\exp(\beta_1) - 1]\cdot 100\% \quad (2)$$

$$CI = [\exp(\beta_1 \pm 1.96SE) - 1]\cdot 100\% \quad (3)$$

where β_1 is the estimate value for moving-average concentration of pollutants and *SE* is the corresponding standard error of the estimate.

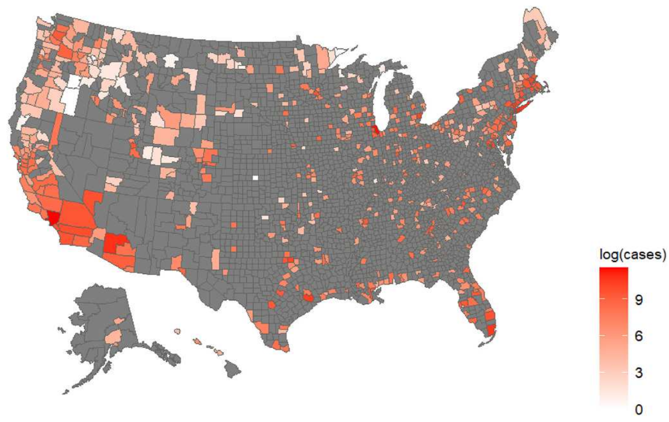
Following the main analysis, a sensitivity analysis was conducted to ensure the robustness of this study. Firstly, correlation between short-term exposure and confirmed cases was explored by a univariate analysis. Data from counties in New York state were removed since it experienced the most severe outbreak of the pandemic in the U.S and the response may not be representative. Including the most severe outbreak region has been shown to strongly affect the analysis (Wu et al., 2020; Xie and Zhu, 2020). Thus, we repeated the above-mentioned analysis excluding counties in New York state. Since previous research has suggested association between long-term air pollution exposure and COVID-19 incidence, to isolate the possible impacts of long-term air pollution, nonattainment counties were excluded, and the GAM model was run again. Nonattainment means an area whose air quality fails to meet the national ambient air quality standard. Lists of nonattainment counties for both $PM_{2.5}$ and O_3 were retrieved from the EPA Green Book (U.S. Environmental Protection Agency, 2020b). In addition, another metric of COVID-19 outcomes, namely confirmed deaths, was analyzed in relation to air pollution exposure. Lastly, the component smooth functions were analyzed and compared with previous studies to ensure the validity of this study. All plots and analyses in this study were executed in R statistical software (version 3.6.1).

3. Results

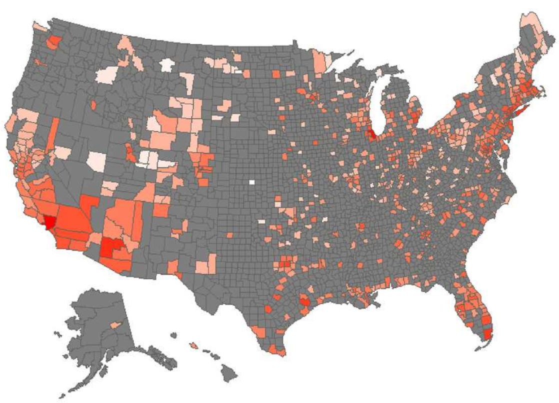
There are 806 (out of 3143) counties included in this study, with 554 counties for $PM_{2.5}$ and 670 counties for O_3, accounting for around 2.1 million cumulative confirmed cases. By June 30th, 2020, there were nearly 2.6 million confirmed cases in the U.S. Thus, this study covers about 80% of total cases. Figs. 1 and 2 illustrate the spatial distribution of short-term mean exposure to $PM_{2.5}$ and O_3 and COVID-19 cumulative confirmed cases. Visual inspection suggests that confirmed COVID-19 cases are higher in the Northeastern, upper Midwest, Gulf Coast, and West Coast regions, where the mean air pollution levels are higher and population density is greater.

To further validate the association, a statistical analysis was carried out to compute the correlation between mean pollution concentration and confirmed cases during the study period. Fig. 3 and Fig. 4 show the scatter plots of the county-level relationship between mean short-term air pollutant concentrations and COVID-19 infection. The red line and shaded area indicate the single-variable regression line and confidence interval. The R values indicate the Pearson correlation coefficients, suggesting how strong the relationships are between mean concentration and COVID-19 infection, with p value representing the level of significance for the coefficient. Both figures show an upward regression line, suggesting a positive relationship. In addition, both R values are positive and p values are smaller than the commonly accepted threshold of 0.05, again confirming the significantly positive association.

Fig. 5 and Fig. 6 show the results for the full models of the main analysis and reduced models of sensitivity analysis where data from New York state or nonattainment counties are removed. For the main analysis, short-term exposure to $PM_{2.5}$ is positively associated with COVID-19 infection at 0.05 significance level. The mean relative risk (RR) is 9.41%, which means that with 10 $\mu g/m^3$ increase in mean $PM_{2.5}$ concentration, the daily confirmed cases increase by 9.41%. The RR value rises and peaks around 5-day lag and 6-day lag and then gradually decreases. While for short-term exposure to O_3, positive associations are presented before the 10-day lag. The mean relative risk (RR) is 2.42%.



(a)



(b)

Fig. 2. Maps show logarithm of cumulative number of confirmed cases during the study period for counties with monitored data of (a) $PM_{2.5}$ and (b) O_3 (highlighted in red). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

The estimated RR peaks at a 2-day lag (4.98%) and decreases thereafter.

As for the reduced model of sensitivity analysis (i.e., excluding New York), the mean RR value for daily $PM_{2.5}$ concentrations grows to 12.64%. The RR rises at the beginning and peaks at the 5-day lag, which is similar to the full model, but stabilize around the peak value after a 5-day lag. The reduced model of short-term exposure to O_3 mimics the performance of the full model, where the mean RR is 2.14% with peak value at 2-day lag (3.81%). To isolate the impacts of long-term air pollution, 14 (out of 554) nonattainment counties for $PM_{2.5}$ and 158 (out of 670) nonattainment counties for O_3 were excluded. The results for short-term $PM_{2.5}$ exposure present a similar pattern to the full model, though with slightly lower RR values with a mean of 9.20%. By excluding all nonattainment counties for O_3, the RR values show a significant decrease compared to the full model. The RR stays positive only before the 3-day lag and drops below zero after an 8-day lag, suggesting a negative association.

Fig. 7 plots the county-level relationship between mean daily air pollution levels and COVID-19 deaths. Short-term exposure to both $PM_{2.5}$ and O_3 is positively correlated with COVID-19 deaths.

Fig. 8 shows the plots of smooth functions for meteorological variables from the 6-day lag $PM_{2.5}$ model, which are representative of all models. The horizontal axis represents meteorological parameters and the vertical axis indicates the dependent variable. Plot (a) suggests that the number of daily confirmed cases decreases with increasing temperature. As for the impact of relative humidity, the plot (b) presents a non-linear relationship. Since the contribution of meteorological parameters is not the focus of this study, the results are compared qualitatively with previous relevant studies to assess the robustness of this study.

4. Discussion

Considering the substantial threats facing global public health, it is pressing to reveal the possible contributing parameters facilitating the spread and course of the COVID-19 pandemic. This study is the first nationwide study in the United States to examine the association between daily $PM_{2.5}$ and O_3 concentrations and COVID-19 confirmed cases. The results suggest that short-term exposure to air pollution, especially to $PM_{2.5}$, is likely to escalate the risk of COVID-19 infection. A significant positive relationship was found, where an increase of 10 $\mu g/m^3$ in short-term exposure to $PM_{2.5}$ is correlated with 9.41% mean increase in the COVID-19 daily confirmed cases across 1 to 14-day lag scenarios. The distribution of the relative risk over the 14-day range peaks around a lag of 5–6 days. The distribution pattern of relative risk mimics the distribution for incubation period of the disease. Studies have found that the range of incubation period falls between 2 and 14 days, with a median or mean value around 5 days (Lauer et al., 2020; Linton et al., 2020). Thus, the pattern of relative risk may reinforce the possible association that most people develop the sympotoms after 5-day exposure to $PM_{2.5}$ pollution. Notably, when data from New York state were removed, the relative risk associated with $PM_{2.5}$ exposure increases

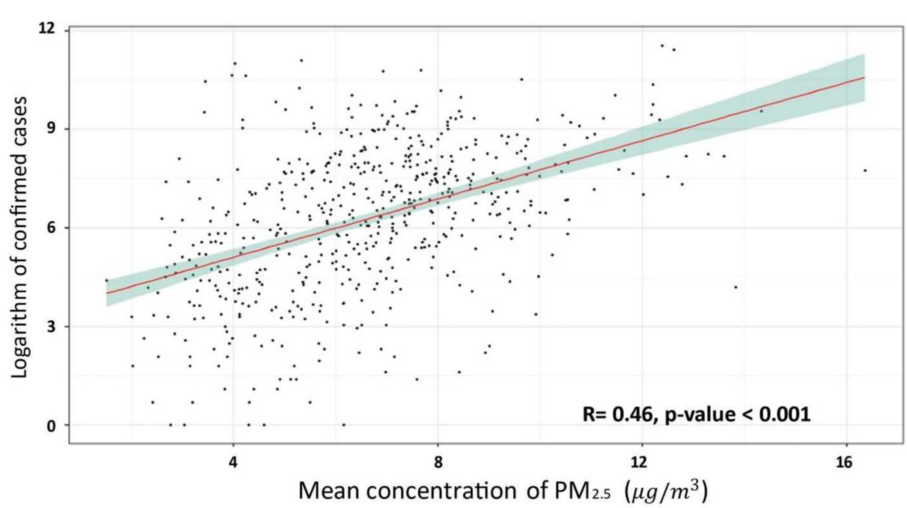


Fig. 3. Correlation between mean short-term $PM_{2.5}$ concentration and logarithm of cumulative confirmed cases.

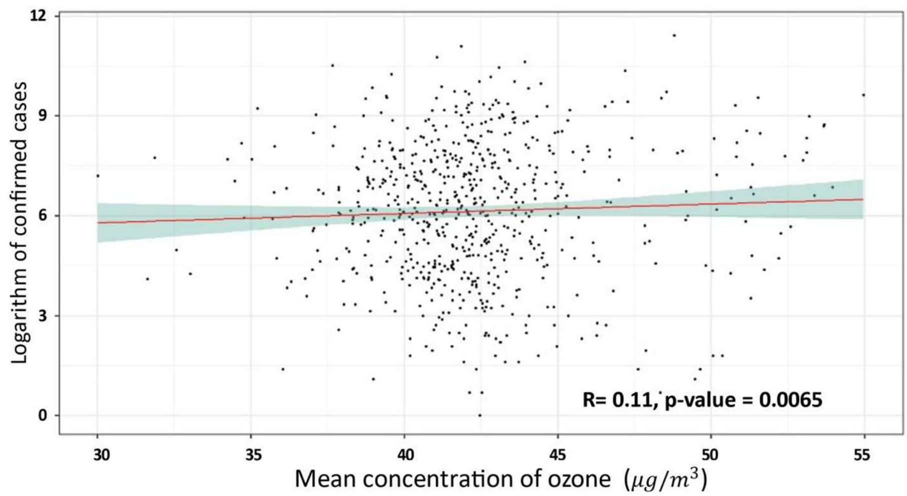


Fig. 4. Correlation between mean short-term O_3 concentration and logarithm of cumulative confirmed cases.

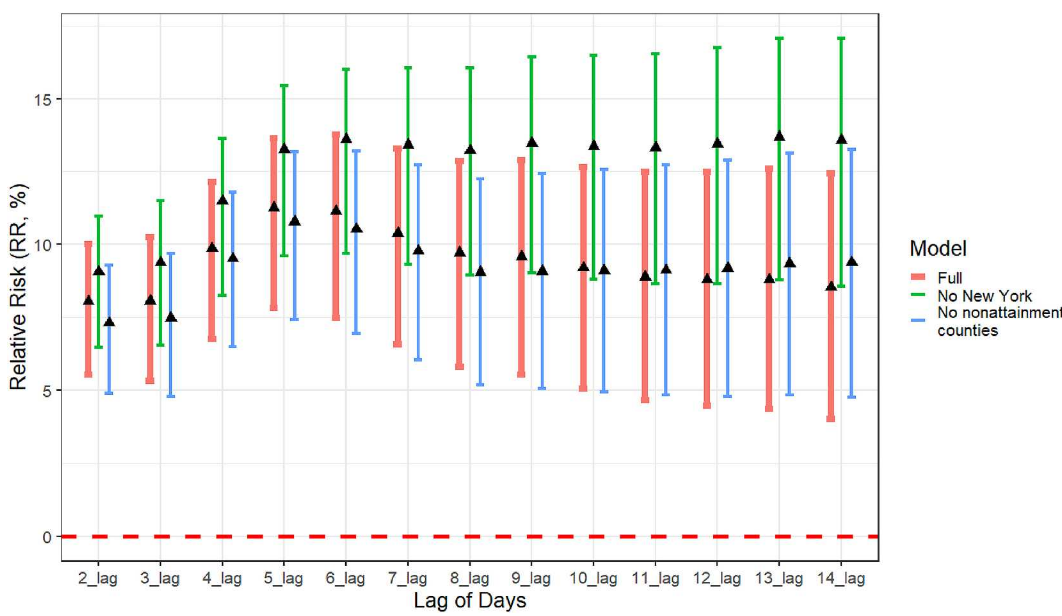


Fig. 5. Daily mean $PM_{2.5}$ concentrations associated Relative Risk (RR) and 95% confidence interval with different numbers of lagged days; the solid triangles indicate the estimate value of RR; the vertical lines are the 95% confidence intervals (red for full model of main analysis; green for model without New York state and blue for model without nonattainment counties of sensitivity analysis). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

and the pattern changes. The reason is not clear. By exluding non-attainment counties, the relative risk slightly decreases but still remains significantly positive, meaning that counties suffering from long-term $PM_{2.5}$ pollution have a higher but non-significant relative risk compared to attainment ones.

Comparatively, the relative risk identified associated with O_3 exposure is much smaller than that of $PM_{2.5}$. An increase of 10 $\mu g/\ m^3$ is correlated with 2.42% mean increase in the COVID-19 daily confirmed cases across 1 to 14-day lag scenarios, where the relative risk of over 10-day lags is not significant. Removing New York state from the analysis yields similar results. The distribution of relative risk is monotonically decreasing after the 2-day lag. After isolating the long-term effects of O_3 exposure, the distribution of relative risk demonstrates a similar but significantly lower pattern and drops below zero after an 8-day lag, which means counties suffering from long-term O_3 pollution have significant higher and positve relative risk than attainment counties. Thus, one of the potential reasons is that exposure to O_3 pollution has an acute and immediate influence and stimulates the symptoms of infected people, and the impacts gradually fade away during longer lagged periods. As for the negative association between short-term O_3 exposure and COVID-19 cases in attainment counties, it might be contributed by the powerful oxidizing and virucidal capability of O_3 (Bayarri et al., 2021). It is important to note that correlation does not indicate causality. O_3 is photochemically produced from the reactions of volatile organic compounds and NO_x. O_3 concentrations have a nonlinear relationship with NO_x emissions, which are dominated by the traffic sector. Thus, varying O_3 concentrations may reflect higher levels of transportation, contributing to case spread of COVID-19. In addition, lower levels of transportation under the restrictions may lead to a slower drop or even an increase in O_3 concentration (Kroll et al., 2020).

The significantly positive association between daily $PM_{2.5}$ and O_3 concentrations and COVID-19 related deaths adds to the validity of this study, which echoes the proposed contribution of air pollution to COVID-19 mortality (Cole et al., 2020; Hendryx and Luo, 2020; Petroni

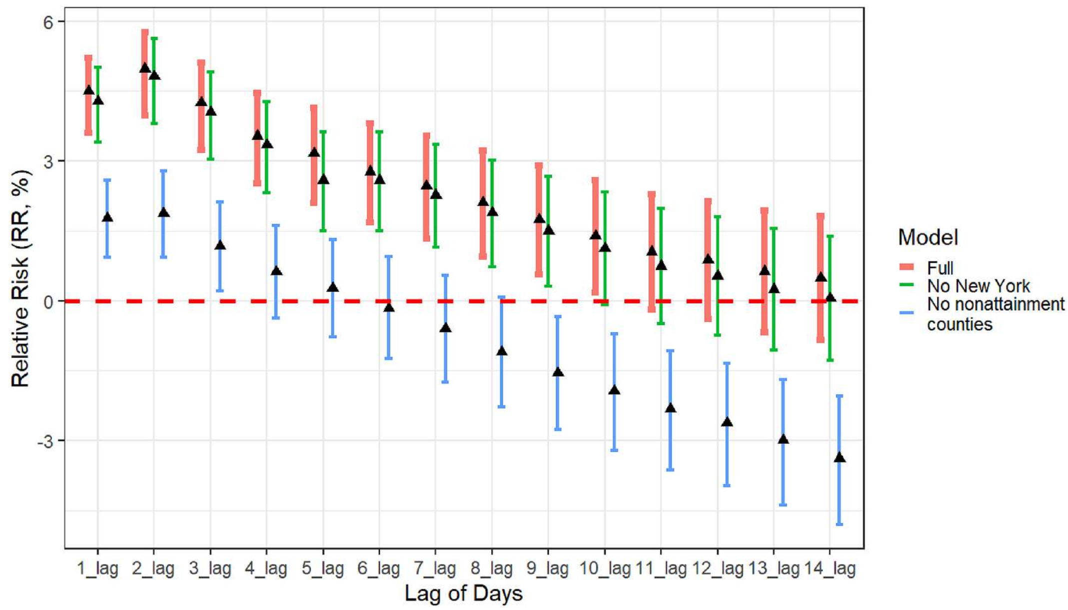


Fig. 6. Daily mean O_3 concentrations associated Relative Risk (RR) and 95% confidence interval with different numbers of lagged days; the solid triangles indicate the estimate value of RR; the vertical lines are the 95% confidence intervals (red for full model of main analysis; green for model without New York state and blue for model without nonattainment counties of sensitivity analysis). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

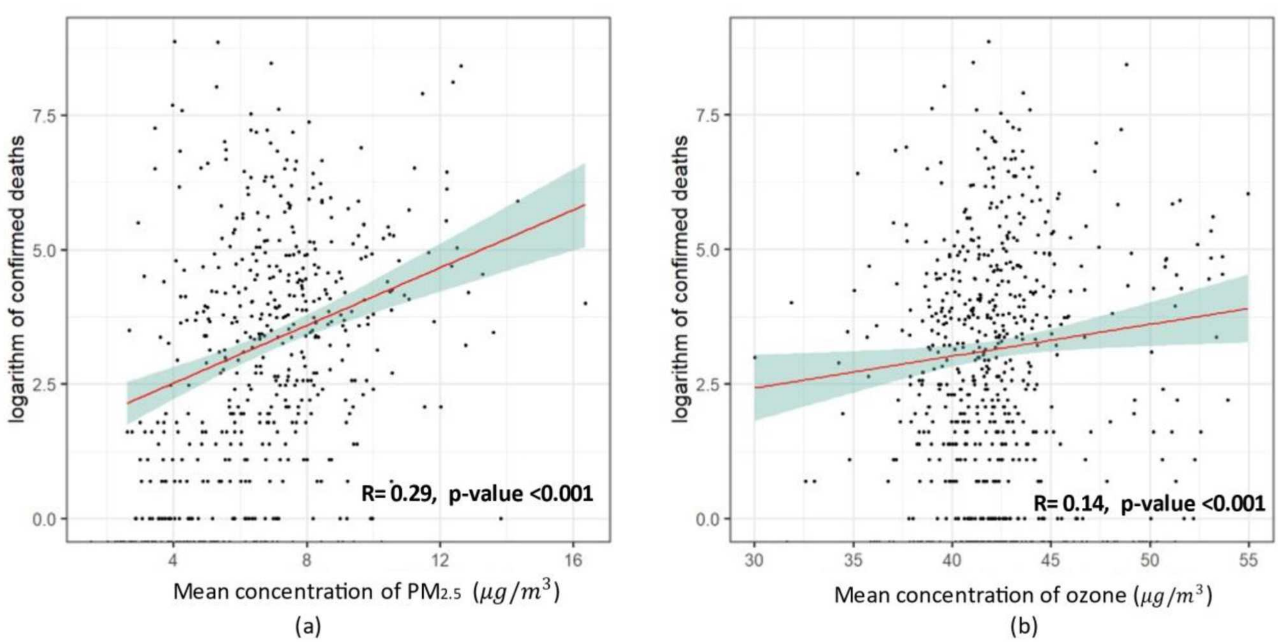


Fig. 7. Correlation between mean short-term (a) $PM_{2.5}$ and (b) O_3 exposure and logarithm of cumulative confirmed deaths.

et al., 2020; Wu et al., 2020). In addition, the negative correlation between mean temperature and COVID-19 infection agrees with findings in China (Li et al., 2020), Brazil (Prata et al., 2020), and the U.S (Wang et al., 2020b). The potential contribution of relative humidity and wind speed identified in this study is relatively small. The results partly acknowledge the results from previous studies that humidity is negatively correlated with COVID-19 prevalence (Ma et al., 2020; Şahin, 2020). The contribution of meteorological parameters to COVID-19 infection is not conclusive yet. Caution should be given to the interpretation of the results from the meteorological variables.

The findings of this study echo previous research findings by recognizing exposure to air pollution increases the severity of contagion outbreak and spread (Cui et al., 2003). The results are in accordance with conclusions from previous studies (Isphording and Pestel, 2021; Li et al., 2020; Zhu et al., 2020) that short-term exposure to $PM_{2.5}$ increases the vulnerability of COVID-19 infection, which contradicts the findings of Azuma et al. (2020). As for the impacts of short-term exposure to O_3, the results of this study agree with those of Zhu et al. (2020) but differ from Isphording and Pestel (2021). Possible confounding factors may be the differences in social context such as hygiene practices and level of obedience to the restriction orders (which have become a contentious political debate in the United States), mean pollution level, and selected pollutants in the analysis. Compared with the only U.S.-context study (Bashir et al., 2020), both studies have identified a significant

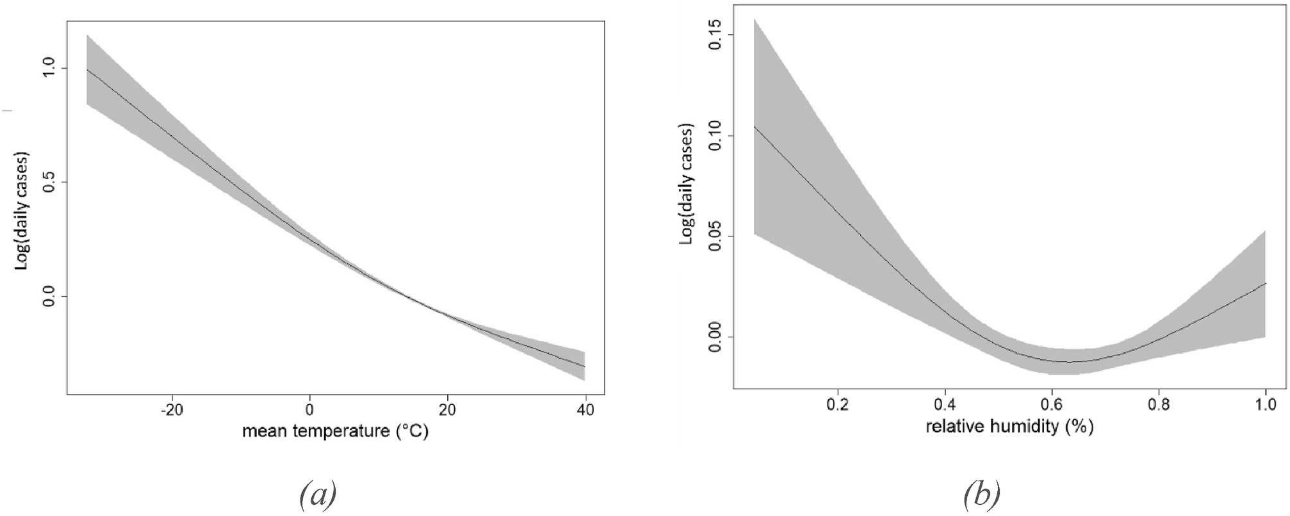


Fig. 8. Plots of smooth function for meteorological variables, with x axis showing the predictor (a) mean temperature, (b) relative humidity and y axis representing the predicted value of dependent variable (logarithm of daily confirmed cases) from the 6-day lag $PM_{2.5}$ model. The solid line indicates the predicted value, and the grey area represents the confidence interval.

correlation between short-term eposure and COVID-19 infection. However, Bashir et al. (2020) identified a negative association, which disagrees with the findings of this study. Since the study of Bashir et al. (2020) applied a correlation analysis in California, possible confounding factors were not considered. Our study offers an in-depth understanding of the association between short-term air pollution exposure and COVID-19 infection for approximately 80% of confirmed cases across the U.S. over the study period.

Though the design of this study cannot provide insights into the causal relationships between short-term air pollution exposure and COVID-19 infection, prior research has proposed several plausible mechanisms that can account for the epedemiological relationships between air pollution and COVID-19 outcomes (Contini and Costabile, 2020; Daraei et al., 2020; Frontera et al., 2020; Isphording and Pestel, 2021; Mehmood et al., 2020; Morawska and Milton, 2020; Tung et al., 2021). It was hypothesized that short-term exposure to air pollution would affect the normal functionalities of our respiratory and pulmonary systems, resulting in lower immune response and inflammation. In addition, particulate matters (PM) could possibly provide adhesion and transportation for the virus, which prolongs the viability duration and travel distance of the virus.

This study faces several limitations to be addressed in future research. Firstly, the coverage area is limited due to data availability and monitoring issues with air pollution data. Thus, not all major regulated pollutants are incorporated in this study. Future works may include additional air pollutant data (e.g., sulfur dioxide or diesel particulate matter (DPM)). Secondly, since the restriction orders strongly influenced people's daily activities, where people were likely to spend less time outdoors, using outdoor air pollution as the measure of exposure may introduce other biases. Thirdly, the ecological analysis used in this study by design cannot control for individual-level confounders like age and medical preconditions. Due to present data unavailability, future research can address this by incorporating individual-level data or conducting experiments.

5. Conclusions

The present global public health emergency brought by COVID-19 not only challenges the medical resource capacities and government responses, but also the strength of scientific research to bring to light important correlations that may explain the transmission mechanisms of the disease. This study is the first nationwide investigation in the United States about the association between short-term exposure to $PM_{2.5}$ and O_3 and COVID-19 confirmed cases. It was found that mean short-term exposure to $PM_{2.5}$ and O_3 is positively related to COVID-19 infection. Relative risk associated with $PM_{2.5}$ exposure is stronger and more evident than O_3 exposure. After isolating the impacts of long-term air pollution exposure, the association between $PM_{2.5}$ exposure and COVID-19 incidence remains positive. On the contrary, relative risks associated with O_3 exposure differ significantly between nonattainment and attainment counties. The findings of this research may assist decision-makers and the public to make more informed decisions regarding their daily activities such as staying at home on polluted days while improving ventilation indoors to minimize the chance of spread and infection. The results further suggest that government agencies may need to take air pollution into consideration when targeting vulnerable groups and allocating medical resources during a pandemic. Alleviation of air pollution and educating the public about its health impacts needs to be prioritized to promote sustainability and public health in the long term.

Credit author statement

Lei Xu: Conceptualization, Methodology, Investigation, Writing-Original Draft Preparation. **John E. Taylor:** Conceptualization, Methodology, Supervision, Writing-Review & Editing, Funding Acquisition. **Jennifer Kaiser:** Supervision, 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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