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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 PM2.5 and 670 counties for ozone (O3), 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 PM2.5/O3 and COVID-19 confirmed cases. The statistically significant results indicate that, with every 10 μg/m² increase in mean pollutant concentration, the number of daily confirmed cases increases by 9.41% (CI: 8.77%-10.04%) for PM2.5 and by 2.42% (CI: 1.56%-3.28%) for O3. The relative risks associated with short-term PM2.5 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 PM2.5, 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 (Hock 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 (Daraci 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 O3 are the two pollutants of major concern. Particulate matter was found...
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, PM10/PM2.5, whose aerodynamic diameter is no more than 10 or 2.5 μm, can cause respiratory tract inflammation and paralyze the ciliated 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 O3. Exposure to O3 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 et al., 2020; Pestel, 2021), significant correlation between short-term exposure and COVID-19 was found in Asia and Europe (National Centers for Environmental Information, 2020). Since AQI is restricted within the U.S. context, after obtaining the daily AQI values of each pollutant, the daily concentration (in μg/m³ units) of corresponding pollutants, which is more universally understandable, was reversely deducted.

The 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.

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 PM2.5 was positively associated with COVID-19 mortality.

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 PM2.5 was positively associated with COVID-19 mortality.

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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 μg/m³ units) of corresponding pollutants, which is more universally understandable, was reversely deducted.

Metereological 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 PM2.5 and O3 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:

\[
\log (case_{it}) = \beta_0 + \beta_1 \text{CPOI}_{l}, \text{lag}_t + s(\text{temp}, 3) + s(\text{RH}, 3) + s(\text{wind}, 3) + \text{county}_{i} + \text{date}_t + \text{DOW} + \log (\text{case}_{i,t-1}) + \epsilon_{it}
\]
results for every 10 \( \mu g/m^2 \) increase for concentration of selected pollutants. The two metrics are calculated as follows:

Relative Risk (RR) = \( [\exp(\beta_i) - 1] \cdot 100\% \)  

CI = \( [\exp(\beta_i \pm 1.96SE) - 1] \cdot 100\% \)

where \( \beta_i \) 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 \( \mu g/m^2 \) 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\%.
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 μg/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 symptom 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.
and the pattern changes. The reason is not clear. By excluding 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 μg/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 significantly higher and positive 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...
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; Sahin, 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

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**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.)

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**Fig. 7.** Correlation between mean short-term (a) PM$_{2.5}$ and (b) O$_3$ exposure and logarithm of cumulative confirmed deaths.
correlation between short-term exposure 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 epidemiological relationships between air pollution and COVID-19 outcomes (Contini and Costabile, 2020; Daraei et al., 2020; Frontera et al., 2020; Isphording and Pestel, 2021; Methordology, 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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