Weather and COVID-19 Deaths During the Stay-at-Home Order in the United States

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Objective: To estimate the association between weather and COVID-19 fatality rates during US stay-at-home orders. **Methods:** With a county-level longitudinal design, this study analyzed COVID-19 deaths from public health departments' daily reports and considered exposure as the 18 to 22 day-period before death. Models included state-level social distancing measures, Census Bureau demographics, daily weather information, and daily air pollution. The primary measures included minimum and maximum daily temperature, precipitation, ozone concentration, PM2.5 concentrations, and U.V. light index. **Results:** A 1 °F increase in the minimum temperature was associated with 1.9% (95% CI, 0.2% to 3.6%) increase in deaths 20 days later. An ozone concentration increase of 1 ppb (part per billion) decreased daily deaths by 2.0% (95% CI, 0.1% to 3.6%); ozone levels below 38 ppb negatively correlated with deaths. **Conclusions:** Increased mobility may drive the observed association of minimum daily temperature on COVID-19 deaths.

Keywords: county, COVID-19, death, minimum daily temperature, ozone, stay-at-home order, US

Understanding the relationship between weather and SARS-CoV-2 transmission has important implications for public health preparedness as the second year of the pandemic draws near. Prior research suggests that weather patterns may influence the transmission of SARS-CoV-2.[1–7] However, research on weather and SARS-CoV-2 transmission has yielded mixed results. Some studies suggested that the virus may follow a seasonal pattern with lower transmission rates during periods of higher temperatures.[8–18] Transmission rates also appeared lower with higher humidity,[9,12–17,19–23] higher ambient U.V. light index[14,17,24] lower wind speed, higher greenness,[25] and lower precipitation.[9,16,23] Other studies, however, reported weak or no relationships between weather metrics and transmission rates.[14,26–31]

Most research on environmental and meteorological effects with COVID-19 fatality has provided simple correlation coefficients or mapped global COVID-19 deaths against the global pattern of temperature changes resulting in predictions that these deaths would increase as the weather became warmer in spring.[32–40] Two time-series studies explored the relationship between temperature changes and COVID-19 deaths for specific cities in China and found that higher temperatures were associated with more deaths.[41,42] Whereas, among the two studies that analyzed international variation in COVID-19 deaths by temperature and precipitation, one found no association,[43] and the other found a negative association.[44] Another study reported no association between COVID-19 deaths and US county-level average summer and winter temperatures, but did find a positive association with historical PM2.5 concentration.[45]

Inconsistent findings on the effect of weather and environmental factors on SARS-CoV-2 transmission and outcomes may emerge from methodological differences. Some studies limited analyses to a small number of environmental factors[12,13,19,21,22,27,46] and did not account for important influences such as government mitigation efforts, public responses, population density, and local practices.[9,13,14,17,21,23,47,48] Additionally, studies of COVID-19 cases suffer from potentially substantial measurement error because testing is not widespread, systematic, or representative, introducing outcome measurement error that differs across space and time and leads to biased estimates. Analyses of COVID-19 deaths, however, can reduce outcome measurement error because COVID-19 deaths frequently occur in a hospital setting, which is presumably an accurate measure of cause of death in the United States and more accurate than COVID-19 case estimates due to many undetected cases. Adequate control of serial correlation is another methodological challenge for time-series data in addition to confounding over time, across geography, measurable and unmeasurable changes in government policies, healthcare resources, testing capacity, and surveillance.

This study aimed to estimate the association of temperature changes on COVID-19 deaths during the states' stay-at-home orders until the start of their reopening, a period with a fairly homogenous policy environment that largely overlapped with springtime in US counties. An aim of this study was to address the methodological issues mentioned above (ie, confounding, serial correlation, and time trends) by using the smallest unit for which national data are available, the county level, and utilizing mixed models to account for county characteristics, time-varying factors, and serial autocorrelation.

METHODS

Study Design

Briefly, county-level daily COVID-19 death data across the United States functioned as the dependent variable, and their

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Biographical sketch:

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Clinical significance: Clinical translation of association between COVID-19 transmission, weather, and air pollution can inform individual behavior and public health policymaking. At individual level, when favorable outdoor temperatures increase contacts, smaller and controlled gatherings are recommended. At policy level, controlling outdoor exposure to certain air pollutants (eg, ozone) may be targeted.

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association with minimum and maximum daily temperatures at the approximate time of exposure to SARS-CoV-2, thought to be approximately 20 days before death,[49–56] were analyzed. A 5-day window around 20 days before death (ie, 18 to 22 days before death) defined the time window when infection began. The analysis accounted for time-constant factors using fixed effects at the county level (eg, population density, demographic factors, political, social, and cultural characteristics) and linear and nonlinear time-varying factors (eg, daily government responses and news events), serial correlation, social distancing measures, and daily levels of precipitation, ozone, PM2.5 (fine particulate matter), and U.V. light.

Data Collection and Refinement

Data from seven different sources were integrated in this study: (1) COVID-19 deaths as reported by the New York Times as of June 30, 2020[57]; (2) county geographic information from the National Oceanic and Atmospheric Administration (NOAA)'s National Weather Service[58]; (3) county demographics from the US Census Bureau[59]; (4) weather from NOAA's Global Historical Climatology Network (GHCN)-Daily data[60]; (5) air pollution from the US Environmental Protection Agency (EPA)[61]; (6) U.V. light from www.openweather.com; (7) and state-level social distancing from a Health Affairs' publication (see Data Sources and eFigure 1 in the eMethods, http://links.lww.com/JOM/A881).[62]

The assembled data file included 3141 US counties. Forty percent of county-days were assigned temperature information from their first nearest weather stations; 21%, 12%, 8%, and 6% of them were assigned temperature information from their second, third, fourth, and fifth nearest weather stations, respectively. The median distance of the first to fifth nearest weather stations from the county centroid was 4.5 (standard deviation of the sample [SD] 6.9), 7.0 (SD, 10.5), 10.1 (SD, 8.1), 11.6 (SD, 6.5), and 12.6 (SD, 6.7) miles, respectively. On the other hand, 71% of county-days were assigned precipitation information from their first nearest weather stations; 19%, 6%, 2%, and 1% of them were assigned precipitation information from their second, third, fourth, and fifth nearest weather stations, respectively. The median distance of the first to fifth nearest precipitation-recording stations from the county centroid was 4.0 (SD, 5.3), 7.6 (SD, 11.7), 10.6 (SD, 11.7), 13.1 (SD, 9.2), and 16.6 (SD, 9.3) miles, respectively. These distances are reasonable averages nationally because if each county were a square, the average distance to the county centroid is 16.5 miles (ie, the United States is 3,531,905.43 sq miles/3242 counties = 33.00 miles × 33.00 miles, distance to the center is ∼16.5 miles).

No county-days were assigned information from a weather station located 60 miles or more away from the county centroid. Among the county-days with missing weather information in the first nearest station, weather station data were reviewed to see if the estimate came from a station that was located 25 miles or more away from the first nearest weather station, and these counties were excluded, resulting in 3088 counties included in the analysis.

Eighty-one percent and 78% of county-days were assigned ozone and PM2.5 information from their first nearest air quality stations, respectively. Nonetheless, the distances of ozone- and PM2.5-recording air quality stations from county centroids were greater than those of weather stations. In the unrefined data file, the median distances for the first and second nearest ozone-recording stations were 27.8 (SD, 51.8) and 35.2 (SD, 41.4) miles, respectively, and 29.7 (SD, 34.0) and 39.3 (SD, 36.4) miles for PM2.5. Such long distances can result in a potentially substantial error in the measurement of air pollutants at the county level. Thus, any county-day that was assigned with ozone or PM2.5 value recorded by a station located 60 miles or more away from the county centroid was dropped. As a result, 605 counties were excluded from the analysis.

Among the remaining 2483 counties in the analysis, counties that had reported zero COVID-19 deaths during the study period beginning date to the start of the reopening period were included. In the final dataset, 1323 counties reported at least one COVID-19 death during the period of this study were included (eFigure 2, http://links.lww.com/JOM/A881). The total number of county-days totaled 59,990 in the final study sample in which the median distances of stations that recorded temperature, precipitation, ozone, and PM2.5 from the county centroid were 6.8 (SD, 5.9), 4.1 (SD, 4.6), 16.8 (SD, 13.7), and 22.2 (SD, 14.2) miles, respectively.

Statistical Analyses

The logarithm of precipitation (plus one) was calculated to normalize the distribution. Estimations for the association between 5-day average minimum daily temperature, 5-day average maximum daily temperature, and the logarithm of COVID-19 daily deaths per adult population occurred through four statistical modeling scenarios (Statistical Modeling section in the eMethods, http://links.lww.com/JOM/A881). As basic control variables, social distancing measures (banning gatherings of 500 or more, closure of public schools, and closure of restaurants, gyms, entertainment facilities), county fixed-effects, and day fixed-effects were included in all model specifications. The preferred statistical model was the fourth model that controlled for the most detailed set of county and time fixed effects, adjusted for precipitation, pollutants, and U.V. index. The estimates and 95% confidence intervals for the 5-day average minimum daily temperature and the 5-day average maximum daily temperature are presented as the percentage change in COVID-19 new daily deaths. Additionally, analyses calculated the 5-day average ozone, PM2.5, and U.V. estimates.

Several sensitivity analyses were conducted. Since ozone and PM2.5 measurements could be taken up to 60 miles away from the county centroid, a considerable error may exist in these measurements, and this is likely a measurement taken outside the respective county. The sample was limited to counties with ozone and PM2.5 values from stations whose maximum distance to county centroid was less than (1) 40 miles and (2) 20 miles to reduce measurement error in ozone and PM2.5 concentrations. The final statistical model was applied to these samples to determine whether or not the association of ozone level and daily COVID-19 death rates persisted. Two sensitivity analyses evaluated different time windows of exposure to SARS-CoV-2 for the weather and air pollution variables. Specifically, the weather and air pollution that occurred in days 8 to 12 (a shorter exposure to death period) and 28 to 32 (a longer exposure to death window) before death were analyzed.

RESULTS

There were 94,044 COVID-19 deaths in the United States by June 30, 2020.[63] The study sample included 64,488 or 68% of these deaths after the exclusions (see Data Collection and Refinement section in Methods). On average, 1.1 (SD, 5.2) new deaths occurred in a county-day of the analysis sample (eTable 1, eFigure 3, http://links.lww.com/JOM/A881). The 5-day mean of minimum daily temperature during the presumed coronavirus exposure window (18 through 22 days before death) was 43.9 °F (SD, 10.9 °F), and the mean maximum daily temperature was 65.4 °F (SD, 11.9 °F). Mean precipitation during the 5-day exposure window was 38.7 mm (SD, 47.6 mm). Among the three meteorological elements, the temperature measures were approximately normally distributed (eFigure 4, http://links.lww.com/JOM/A881). The 5-day mean of 8-hour maximum concentration of the ground-level ozone during the exposure period was 41.2 ppb (SD, 5.7 ppb). Ozone levels were most frequently in the ‘‘Good’’ AQI (air quality index) range.[64] The mean daily PM2.5 concentration during the exposure period was 6.6 $\mu g/m^3$ (SD, 2.8 $\mu g/m^3$), and 7.1 for the average U.V. light index (SD, 1.8) (eTable 1, eFigure 4, http://links.lww.com/JOM/A881).

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TABLE 1. Change in Daily Deaths for a One-Unit Change in Weather and Air Quality (County-days of Observation, $N = 59{,}990$)

Variables	Model 1	Model 2	Model 3	Model 4	Model 4 + Prec.	Model 4 + Prec. + O_3	Model 4 + Prec. + O_3 + PM2.5	Model 4 + Prec. + O_3 + PM2.5 + UV
Average minimum temperature, F	0.035	0.032	0.020	0.019	0.019	0.013	0.013	0.012
95% CI	(0.023, 0.047)	(0.020, 0.044)	(0.006, 0.034)	(0.005, 0.034)	(0.004, 0.033)	(−0.002, 0.0283)	(−0.002, 0.027)	(−0.003, 0.027)
Average maximum temperature, F	−0.021	−0.018	−0.010	−0.008	−0.006	0.001	0.001	0.000
95% CI	(−0.030, −0.011)	(−0.028, −0.009)	(−0.021, 0.001)	(−0.019, 0.004)	(−0.018, 0.006)	(−0.012, 0.013)	(−0.011, 0.013)	(−0.012, 0.012)
Log(Average Precipitation [mm] + 1)					0.014	0.009	0.010	0.010
95% CI					(−0.014, 0.042)	(−0.020, 0.037)	(−0.019, 0.039)	(−0.019, 0.039)
Average ozone concentration, ppb						−0.019	−0.019	−0.018
95% CI						(−0.030, −0.007)	(−0.030, −0.007)	(−0.030, −0.007)
Average PM2.5 concentration, $\mu g/m^3$							0.006	0.005
95% CI							(−0.017, 0.028)	(−0.018, 0.027)
Average U.V. light index								0.049
95% CI								(−0.124, 0.222)
Set of geographical and time controls:								
Social distancing measures	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
US-level day fixed-effects	Yes	Yes						
Region-level day fixed-effects			Yes	Yes	Yes	Yes	Yes	Yes
County-specific time-trends		Yes		Yes	Yes	Yes	Yes	Yes
R-squared	0.030	0.083	0.048	0.101	0.101	0.101	0.101	0.101

Note: Social distancing measures include (1) order of no gathering of more than 500 people, (2) order of public school closures, and (3) order of closure of restaurants, entertainment venues, and gyms. The averages are taken over the 5-day exposure period (ie, days 18 to 22 before birth). The number of counties in the sample is 1323.

Temperature Results

In the basic model that included US-level day fixed-effects, a 1 °F increase in average minimum daily temperature within the 5-day exposure window was associated with a 3.5% (95% confidence interval [CI], 2.3% to 4.7%) increase in adult COVID-19 deaths for a typical US county during the study period (Model 1, Table 1). Also, a 1 °F increase in average maximum daily temperature across the 5-day exposure window was associated with a 2.1% decrease (95% CI, 1.1% to 3.0%) decrease in adult COVID-19 deaths during the study period (Model 1, Table 1).

The magnitude of the associations of COVID-19 deaths with the average minimum and maximum daily temperatures during the 5-day exposure period was attenuated slightly with the inclusion of county-specific time trends (Model 2, Table 1). In contrast, inclusion of region-level day fixed-effects noticeably changed the association of COVID-19 deaths with the temperature measures (Model 3, Table 1). When additionally accounting for county-specific time trends, the association between minimum temperature and COVID-19 deaths did not change substantially, but the negative association of COVID-19 deaths with maximum daily temperature was no longer statistically significant (Model 4, Table 1). The association of COVID-19 deaths with maximum daily temperature approached zero and remained statistically insignificant with the inclusion of precipitation, ozone, PM2.5, and U.V. index in Model (4). The association of COVID-19 deaths with minimum daily temperature was attenuated to 1.2% (95% CI, −0.3% to 2.7%) for a 1 °F increase in the 5-day average (columns 5–8, Table 1).

Next, associations between minimum daily temperature and COVID-19 mortality for county-days stratified by 1 °F of the 5-day average minimum daily temperature were estimated. The association differed between cooler and warmer counties with a 5-day average minimum daily temperature of at least 35 °F—approximately its 25th quantile, below which the analysis sample becomes too small to render statistical power for estimations. The analysis revealed a range of 5-day average minimum daily temperatures between 53 °F and 63 °F, in which COVID-19 deaths were positively associated with minimum daily temperature, and the estimated size of the associations ranged from 1.7% (95% CI, 0.3% to 3.3%) to 2.2% (95% CI, 0.4% to 4.0%) (Fig. 1). In sensitivity analyses with temperature exposure 10 days before and 10 days after the presumed exposure window (ie, days 18–22 before deaths occurred), no statistically significant associations occurred (eFigure 5, http://links.lww.com/JOM/A881).

Air Pollutants and U.V. Results

The inclusion of ozone in Model (4) had the greatest influence on the association of county-level COVID-19 deaths with minimum daily temperature and resulted in a 32% decrease in the magnitude of the association for minimum daily temperature (columns 5–6, Table 1). Ozone had a statistically significant association with decreased COVID-19 deaths. Each 1 ppb increase in the average ozone concentration during the presumed 5-day exposure period was associated with a 1.8% decrease (95% CI, 3.0% to 0.7%) in county-level COVID-19 deaths (columns 6–8, Table 1).

The potential that this inverse association between ozone and COVID-19 deaths occurred as a result of an area's level of pollution received further scrutiny. The analysis further restricted observations to those with maximum average daily ozone measurements that occurred between 25 ppb (25th quantile) and 45 ppb (90th percentile). Then, Model (4) was estimated again as the county-day inclusion criterion was expanded by 1 ppb until the lowest average maximum daily ozone level was 45 ppb—its 90th

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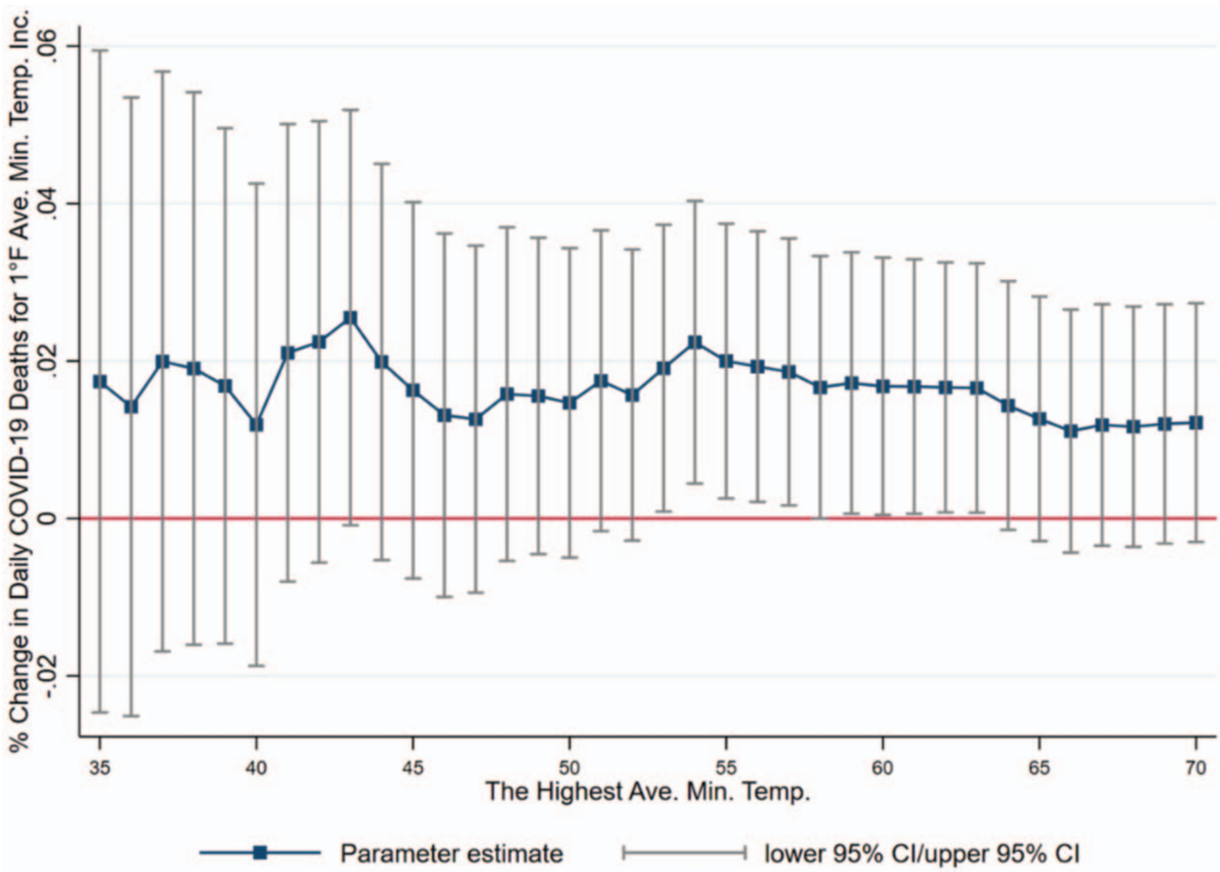

FIGURE 1. Percentage change in deaths as predicted by minimum daily temperature. Note: These are percentage (in decimals) changes in daily deaths per 18+ county population for a 1 °F increase in the 5-day average of minimum daily temperature in days 18 to 22 before death, stratified by county-days based on their highest average minimum temperature.

percentile, above which the analysis sample becomes too small to provide statistical power for estimations. The analysis showed that county-level COVID-19 deaths were negatively associated with minimum daily ozone concentration for counties with ozone below 38 ppb. In counties with ozone below 38 ppb, a 1 ppb increase in 5-day ozone concentration was associated with 2.0% fewer COVID-19 deaths (95% CI, 0.1% to 3.6%) (Fig. 2).

Sensitivity analyses showed no statistically significant associations between COVID-19 deaths and 5-day average ozone level 10 days before and 10 days after the presumed exposure window (ie, days 18–22 before deaths occurred) (eFigure 6, http://links.lww.com/JOM/A881).

In another set of sensitivity analyses, the magnitude of the association between ozone and COVID-10 fatalities remained largely the same for samples with a pollutant monitor within 20 miles and within 40 miles (eFigure 7, http://links.lww.com/JOM/A881). In fact, the results became stronger for both the 20-mile and 40-mile samples (eFigure 7, http://links.lww.com/JOM/A881).

DISCUSSION

The examination of the association between weather changes and US COVID-19 fatality rates only appeared to be associated with minimum temperature and ozone levels. This analysis showed an increase in the minimum daily temperature during the stay-at-home period was associated with higher COVID-19 fatality rates for areas where the minimum daily temperature ranged between 53 °F and 63 °F. Additionally, higher ozone levels were associated with fewer COVID-19 deaths in areas with ozone below 38 ppb. Analysis found no statistically significant relationship between maximum daily temperature, precipitation, U.V., and PM2.5 and county-level COVID-19 deaths during the study period.

Findings within the literature on the association of COVID-19 transmission and fatality with temperature has been mixed.[8,9,12–17,26–28] The present analysis aligned with international studies that predicted the association between increasing temperature and higher deaths.[32,65] Prior studies showed that related coronaviruses were influenced by temperature.[1–7] Specifically, evidence suggested higher prevalence rates of SARS-CoV-1 in 2002 and 2003 in areas with lower temperatures and with a wider range between daily minimum and maximum temperatures as compared with areas with a more narrow range between minimum and maximum temperatures.[4] The highest prevalence of SARS-CoV-1 occurred when temperatures averaged 62 °F[4] which coincides with the range observed in the present investigation which further highlighted a positive association with COVID-19 fatalities. Also, higher temperatures were associated with higher MERS-CoV transmission rates, a virus similar to SARS-CoV-2.[5–7]

The range of minimum temperatures (ie, 53 °F to 63 °F) for which we observed a statistically significant association with increased COVID-19 deaths fell below the range of temperatures in which SARS-CoV-2 becomes unstable with shortened survival times on surfaces and in aerosols (86 °F or higher).[66,67] The positive association between COVID-19 deaths and minimum daily

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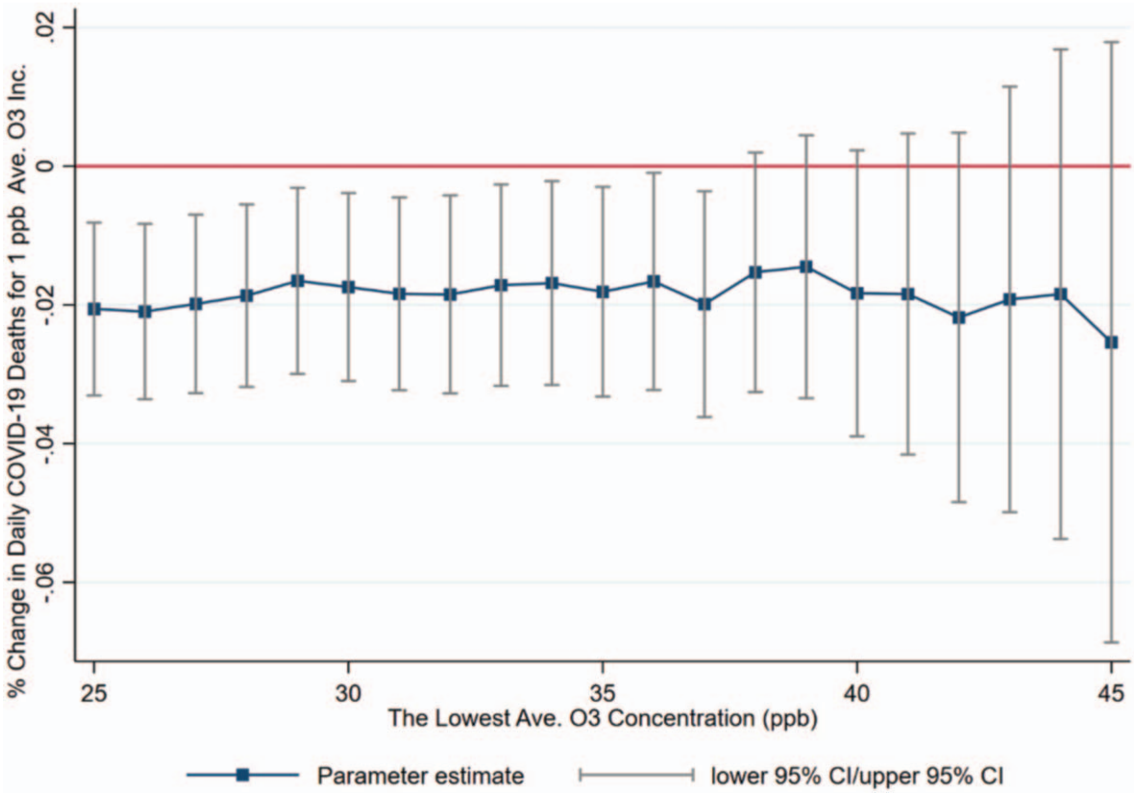

FIGURE 2. Percentage change in deaths as predicted by maximum daily ozone. Note: These are percentage (in decimals) changes in daily deaths per 18+ county population for a 1 ppb increase in the 5-day average of maximum daily ozone level in days 18 to 22 before death, stratified by county-days based on their lowest average maximum daily ozone level.

temperature for areas within the range of 53 °F to 63 °F may be attributable to increases in physical mobility and contact rates during such temperate days. Increased minimum temperature in the springtime in the northern hemisphere may be a reason people leave their homes more often than in colder temperatures early in the year, a behavior in line with the findings of human activity analyses.[68,69] Temperature (minimum) may have distinct effects on behavior in summer or winter climates.

Areas with high levels of ozone, for which a major source of ozone is automobile emissions, are associated with increased levels of respiratory diseases, such as asthma, but the negative association between the ground level ozone level and COVID-19 deaths indicates a potentially protective dynamic. Municipal sanitizing systems often use ozone to disinfect water sources or, in some health care settings, to disinfect surfaces. Laboratory testing shows that ozone may inactivate SARS-CoV-2.[70,71] Currently, researchers are exploring an ozone-based intervention to curb the progression of COVID-19.[72] Published literatures documents a negative crude correlation between average ozone level in major Chinese cities in January and March 2020 and confirmed COVID-19 cases.[73] Also, a global study showed a negative association between COVID-19 transmission rates and ozone concentration.[17] The present analysis provides empirically robust evidence of a relationship between ozone and COVID-19 deaths that warrants replication in future research; however, chance may also explain this finding, and this association may also be indicative of reverse causation where counties with high COVID-19 fatality stopped commuting via automobiles.

There are several limitations to this study. The present study restricted analyses to counties within the United States, so they may not extrapolate to other countries. Also, in accordance with the literature, this study assumed the number of days from SARS-CoV-2 exposure to death was 18 to 22. The period includes incubation and symptom onset-to-death periods for which wide ranges are reported.[49–56] Therefore, it is possible that the exposure-to-death period is longer or shorter than the presumed 18 to 22 days. We retain confidence that this window is the likely period of exposure since no statistically significant associations arose after adjusting the time period. Another limitation is measurement error in the assignment of ozone and PM2.5 concentrations since analysis utilized monitors quite far away from county centroids. This may contribute to the lack of an observed association between PM2.5 and COVID-19 mortality reported elsewhere.[45]

In conclusion, we observed that within county-days where the minimum temperature was between 53 °F and 63 °F, temperature changes were positively associated with COVID-19 deaths. This study suggests that temperate temperatures may be influencing SARS-CoV-2 transmission and fatality likely due to impacting social behaviors, such as increased mobility and increasing contacts, during temperate temperatures. The effect of ozone on COVID-19 deaths may be related to its disinfectant properties, but this requires further confirmation.

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