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Effects of Short-Term Air Pollution Exposure on U.S. COVID-19 Mortality

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Abstract

Importance: Prior studies have shown that long-term exposure to air pollution predicts higher COVID-19 mortality, but there is limited evidence on the effect of short-term fluctuations in air pollution levels.

Objective: To determine whether short-term changes in county air-pollution levels predict COVID-19 mortality in the U.S.

Design: We use county-level data regarding COVID-19 deaths, air pollution, temperature, precipitation, and lagged SARS-CoV2 infection and vaccination rates, with county and date fixed effects, to assess whether, and for how long, variation in local air pollution predicts COVID-19 mortality rates.

Setting: We use county-by-day data on COVID-19 deaths, infections, and vaccination rates, the aerosol optical depth (AOD) measure of daily air pollution from NASA MODIS satellite data, and Oregon State University PRISM database on daily precipitation and temperature, over March 2020 through August 2021.

Participants: 2,942 U.S. Counties with data on COVID-19 mortality and air pollution levels, after interpolation for days with missing pollution data.

Exposures: Daily air pollution levels; lagged daily COVID-19 infection and vaccination rates.

Main Outcomes and Measurements: County-level COVID-19 deaths measured as the natural log of (7-day moving average daily deaths +1).

Results: Higher AOD levels predict modestly higher COVID-19 mortality for the next 2-3 weeks, controlling for local lagged infections, lagged vaccination rates, temperature, and precipitation. A one-standard-deviation increase in AOD over the previous 14 days predicts 5.9% higher COVID-19 mortality.

Conclusion and Relevance: The evidence in this study on the association between higher near-term air pollution and COVID-19 mortality suggests that persons who are infected with or at risk for SARS-CoV-2 infection should limit their exposure to air pollution. Paying greater attention to indoor ventilation and air filtering, including in hospitals, may reduce COVID-19 deaths.

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Key Points

Question: Does short-term variation in air pollution predict variation in COVID-19 mortality?

Findings: Fluctuations in county-level daily air pollution, relative to the county-mean, predict higher COVID-19 mortality for the next 2-3 weeks.

Meaning: Efforts to reduce air-pollution exposure, especially for already infected COVID-19 patients, can significantly reduce COVID-19 mortality.

Tweet: Daily changes in local air pollution levels predict COVID-19 mortality for the next 2-3 weeks.

Introduction

Knowing whether a significant association exists between short-term air pollution exposure and COVID-19 mortality is important to guide individual efforts to limit pollution exposure and efforts by governments and hospitals to improve ventilation and air filtering. Both long-term ambient air pollution levels and short-term spikes in pollution can lead to higher mortality from respiratory illness,[1-3] and higher healthcare spending.[4] Several studies have documented an association between long-term air-pollution levels and COVID-19 mortality.[5-11]

In contrast to the evidence on long-term air pollution exposure, the relation between short-term exposure to air pollution and COVID-19 mortality risk is less understood. One German study uses wind direction as an instrumental variable for pollution levels and finds that short-term exposure predicts higher mortality over a limited period early in the pandemic.[13] An Italian study found an association between monthly average air pollution and COVID-19 mortality over March-June 2020,[14] but did not control for geographic region, so the observed association could reflect urban areas being both more polluted and having more COVID-19 cases due to initial spread principally in urban areas. US evidence is very limited. A single-county study of Queens, New York, early in the pandemic, found no association between pollution levels and mortality.[15] A California study during March-April 2020 found an association between average pollution levels, apparently averaged over the sample period, and COVID-19 mortality over this period.[16] As with the Italian study,[14] this could reflect urban areas being both more polluted and having more COVID-19 cases during this period.

We study the relation between short-term air pollution exposure and COVID-19 mortality rates over the continental U.S. (48 states plus D.C.), from pandemic onset in March 2020 through August 2021. Our study thus provides a much more complete picture of the association between short-term fluctuations in air quality and COVID-19 mortality. We assess whether county-by-day pollution levels predict future COVID-19 deaths in a model with county fixed effects (which control for average pollution levels over our sample period and other time-invariant county characteristics), date fixed effects, and relevant time-varying covariates (lagged infection rate, lagged vaccination rate, precipitation, temperature).

Methods

We study the relation between short-term air pollution and COVID-19 mortality and infection rates using daily data on satellite-measured aerosol levels and county-level COVID-19 mortality, infection, and vaccination rates. We construct a panel dataset on a county-by-day basis covering the continental United States (48 states plus D.C.) from March 2020 to August 2021.

Environmental Data

Data on air pollution come from the Moderate Resolution Imaging Spectroradiometer (MODIS) on NASA's Terra satellite. We use MODIS data on Aerosol Optical Depth (AOD) to measure air pollution. AOD is available on a daily basis with geographical resolution of 3 km^2. Data on AOD is available for about half of US counties on any given day, depending on cloud cover and satellite flight patterns. AOD is a unitless measure, higher AOD indicates higher aerosol concentration, and thus higher pollution levels. The average county-level AOD for our full sample is 0.29. For comparison, the average AOD in highly polluted northern India over 2005-2018 was around 0.50.[17] AOD is a good predictor of suspended particulate matter.[18,19]

We obtain information on temperature and precipitation from the Parameter-elevation Regressions on Independent Slopes Model (PRISM), a spatial climate database maintained by Oregon State University, providing grid data at a resolution of 4 km^2.

We map AOD and weather data to counties following a geographical weighted average method used by the previous literature.[20] See Appendix sections 3-4 for details on AOD and this mapping.

COVID-19 *Data*

We obtain daily data on county level COVID-19 cases and mortality from the New York Times website, which in turn collects data from state and local governments and health departments. The data is available as daily counts and 7-day running averages; we use the 7-day averages.

We obtain county vaccination rates from the Centers for Disease Control and Prevention (CDC).

Outcome (COVID-19 Mortality)

Our main outcome variable is county-level COVID-19 daily mortality. Due to the weekly reporting schedule of many states (most states do not report COVID-19 data on weekends and holidays; Florida only reports on Friday; Kansas, Michigan, and Iowa only report on Monday, Wednesday, and Friday), daily mortality and case counts are noisy. Therefore, we use daily 7-day moving averages, which smooth the daily counts and remove the cyclical weekly pattern. We measure county mortality in logs, but add one before taking logs to avoid losing observations with no deaths. Because the outcome is in logs, the coefficients on the predictor variables can be roughly interpreted as fractional changes in predicted mortality.

Based on evidence that the concentration-response effect of air pollution for other respiratory disease is close to exponential shape (marginal damage from pollution increases with pollution level,[21,22] we take the natural log of daily moving average mortality. To prevent losing observations with zero value, we arbitrarily add 1 to the outcome variable before taking logs, but in the Appendix, Figure A11, assess robustness if we instead add 0.1.

Statistical Analysis:

We use a multivariate linear model with two-way fixed effects (county and date), applied to our longitudinal data, to estimate the conditional correlation between daily 7-day moving average COVID-19 mortality and lagged daily air pollution, using lags of 1 to 28 days (see regression details in Appendix Section 6). The county fixed effects control for county characteristics that vary slowly, if at all, over our time period, including long-term pollution level, poverty level, urban vs. rural character, population density, and racial and ethnic composition. The date fixed effects control for seasonality, and our use of a 7-day moving average for deaths and infections controls for day of week effects in either actual or reported infections and mortality. Thus, we measure the effect of changes in pollution levels, relative to the county mean over the sample period and the daily mean for the country. The outcome variable is log of county-by-day COVID-19 daily deaths (7-day moving average, plus one to avoid missing values). In robustness checks we assess shorter lag periods (14 and 7 days).

We control for confirmed infections, lagged 18 days (7-day moving average) to account for the level of COVID-19 infections in the county, but consider shorter and longer lags in robustness checks. We also control for the county vaccination rate lagged 18 days to allow time for vaccination to affect infection and mortality rates;[23] and lagged weather conditions (average precipitation and temperature for past two weeks). The sample period is March 1, 2020 (the rough onset of the pandemic) to August 26, 2021. We cluster standard errors at the county-level.

We lag infection rates and vaccination rates by 18 days based on studies which found that for COVID-19 decedents; the average duration from symptom onset to ICU admission is 11 days;[24] the average duration from ICU admission to death is 7 days;[24] and the average duration between COVID-19 diagnosis and death was 18.1 days.[25]

We present principally graphical results, in which we plot the estimated daily coefficients of lagged daily air pollution, as predictors of current COVID-19 mortality. We also report regression analyses. In the regressions, the core predictor variable for COVID-19 mortality is the fraction of days over the last three weeks in which the county had AOD greater than the national median. We call this variable "High Pollution Exposure." In robustness checks, we vary the number of days over which this variable is measured.

Addressing missing AOD observations

A central challenge for this study is how to handle missing data. AOD data is measured by satellite sensors from orbit. Both heavy cloud coverage and bright ground surface (i.e., water surface, snow coverage, and urban areas) can cause difficulty for satellite sensors and lead to missing observations. To estimate daily coefficients on lagged AOD, we need complete data on AOD over the period being studied (over lags of up to 28 days). However, long periods without missing AOD (due principally to cloud cover) are rare in the Eastern United States. To obtain a nationally representative sample, we use linear interpolation of AOD for either 1 or 2 days, based on AOD for the days immediately preceding and following the missing day(s). We also present results where we do not interpolate but measure AOD only every 3 days, which reduces the need for interpolation.

Rural-Urban and East-West Comparisons

We also assess whether the predictive power of AOD for county mortality differs between urban and rural areas. With 2-day interpolation, we have data for at least some time periods for 2,942 counties, out of 3,103 counties in the U.S. We define urban counties (1,088 counties in our sample) as those included in a Combined Statistical Area, as defined by the Census Bureau (basically, any county in or close to a metropolitan or micropolitan statistical area); the remaining 1,854 counties are rural. We modify our basic approach above to include lagged AOD levels measured separately for urban and rural counties. We proceed similarly to assess whether the predictive power of AOD is similar in Eastern counties (1,882 counties) versus Western counties (1,060 counties).

Results

Summary Statistics

We provide summary statistics in Table 1 for all counties and for each interpolation choice. The full dataset has 859,001 non-missing observations of AOD for 3,103 counties (out of 1,691,135 possible observations if AOD were never missing) over March 1, 2020 to August 26, 2021. However, sample size drops dramatically if we require 28 consecutive days of AOD data preceding the day when mortality is measured, to only 24,583 observations of 491 counties, almost all in the western U.S. (see Figure 1). Our interpolation strategy (2-days versus 1-day versus no interpolation but measuring AOD only every three days) allows us to study a much more nationally representative sample. The additional counties that we capture through interpolation on average are smaller, and have lower mortality and infection counts, but somewhat higher mortality and infection rates.

Figure 1 Panel A shows which counties are usable in our analysis (have at least one day in our sample period with non-missing AOD for the preceding 28 days), with each of: (i) no interpolation; (ii) 1-day interpolation; (iii) 2-day interpolation; and (iv) not interpolating, but requiring AOD data only every 3 days. This figure shows the loss of sample in the Eastern U.S. with no interpolation, recovery of a nationally representative sample with 2-day interpolation, and partial loss of sample in the Eastern U.S. with either 1-day interpolation or the every-3-days approach.

Figure 1 Panel B shows the national daily trend of county-average AOD data without interpolation. The average over our full period is 0.29. There are notable spikes in the summers of 2020 and 2021, coincident with large wildfires in the West. The smoke from these fires strongly affected the West, but it was also blown east by prevailing winds, leading to higher AOD levels in the Midwest and, to a lesser extent, the East.

Main Results

In Figure 2, we plot the coefficients and associated 95% confidence intervals (CIs), from a regression which predicts daily county mortality (log of 7-day moving average +1) based on lagged daily AOD over the prior 28 days, with county and date fixed effects and the covariates discussed above. Panel A uses 2-day interpolation; Panel B is similar but uses 1-day interpolation; Panel C does not use interpolation, but we measure lagged AOD only every 3 days. We present results with no interpolation in Appendix Figure A5. Results are consistent across all panels. Lagged AOD predict significantly higher current mortality for lags up to about 3 weeks, with somewhat lower but still statistically significant coefficients in the third week (lags of 15 days or more), and insignificant coefficients after that. This time lag is consistent with the typical lag from symptomatic infection to death. The coefficients of lagged daily AOD with 2-day interpolation range between 0.0030 and 0.0061 over lags of 1-14 days (mean of daily coefficients = 0.0042). This implies that a one standard deviation (0.395) increase in AOD for a single day during the prior two weeks predicts a modest (0.12% to 0.24%) increase in daily mortality. The coefficients in Panel C are roughly 3 times larger, because we are using one-third as many days with lagged AOD to predict mortality. If we sum the daily coefficients over 1-21 days, exposure to one standard deviation higher AOD throughout this period predicts a 3.15% increase in COVID-19 mortality (95% CI, 1.97-4.34%).

In Table 2, we report results, with two-way fixed effects, using High Pollution Exposure as the predictor variable, measured over a 3-week period (the rough period for which daily results are significant in Figure 2 with 2-day interpolation). We present results with 2-day interpolation, 1-day interpolation, and measuring AOD every 3 days. Columns (1)-(3) present results for High Pollution Exposure, with the lagged county infection rate as the only time-varying covariate. Both High Pollution Exposure and lagged cases predict higher mortality. In columns (4)-(6) we add lagged vaccination rate and 2-week average precipitation and temperature as additional covariates. The lagged vaccination rate predicts lower mortality, as expected.

Across specifications, higher values for the High Pollution Exposure measure, relative to each county's mean (absorbed by the county fixed effects) and the daily mean (absorbed by the day fixed effects) predict significantly higher COVID-19 mortality. The 0.0509 point estimate in column (4), with full covariates and 2-day interpolation, implies that going from 0 to 21 days with air pollution above the national mean for that day predicts 5.22% higher COVID mortality.

Urban versus Rural; East versus West

In Figure 3, Panel A, we show coefficients on lagged AOD separately for urban and rural counties. The predictive value of AOD, and the lag period over which AOD predicts COVID-19 mortality, are similar in urban and rural areas. In Figure 3, Panel B, we compare the Eastern U.S. and Western U.S., and find similar coefficients on lagged AOD in both areas.

Robustness Checks

We conduct a number of robustness checks, and report results in the Appendix. We obtain consistent results if we: (i) study a shorter period for lagged AOD of either 14 or 7 days instead of 28 days (Appendix Figures A6-A7); (ii) either omit lagged cases as a covariate, or use lags of 9 or 27 days instead of 18 days (Appendix Figures A8-A10); (iii) add 0.1 instead of 1 before taking logs in measuring mortality (Appendix Figure A11); (iv) measure High Pollution Exposure over 7 or 14 days, instead of 21 days (Appendix Table A1). We also cluster standard errors at the state instead of the county level (Appendix Figure A12); the standard errors are larger but inference is similar.

Discussion

We found that short-term increases in AOD, which provides a daily measure of pollution exposure, predict higher COVID-19 mortality over the next 2-3 weeks within a county, relative to county means and the national daily mean, controlling for cases, temperature and precipitation. The county fixed effects included in our analyses control for time-invariant local factors that may affect the number of deaths, such as county population, long-term pollution levels, poverty, and racial/ethnic composition.

Air pollution fluctuations within each county should be largely uncorrelated with other factors known to predict COVID mortality rates. If so, then the association between pollution and mortality would be causal: higher short-term air pollution causes higher COVID mortality. Our results provide empirical support for the importance of limiting pollution exposure during high-pollution periods, especially during periods when COVID-19 infection rates are also high, and especially for individuals at high risk of COVID-19 mortality.

The empirical magnitude of the mortality effect we report is modest. A one standard deviation increase in AOD, sustained over three weeks, predicts 3.15% higher COVID-19 mortality. But even this modest magnitude is important, when measured against the large number of COVID-19 deaths.

Our study extend understanding of the link between short-term pollution levels and COVID-19 mortality in several aspects. First, this is the only national study in the United States and covers an extended period from March 1, 2020 through August 26, 2021. Prior studies cover small regions for short time periods early in the pandemic. Second, because we use national AOD data, rather than ground-based air monitors (usually located in urban areas), we are able to study both rural and urban areas. Third, we show that the relation between daily air pollution levels and COVID-19 mortality persists for up to three weeks following the exposure.

Looking beyond COVID-19, both long-term and short-term exposure to air pollution are respiratory health concerns. For example, asthma, COPD, lung cancer, and respiratory infections are exacerbated by exposure to a variety of air pollutants, especially particulates, ozone and nitrogen oxides.[26] Air pollution levels have been linked to acute lower respiratory infections in young children,[27] and increased pneumonia and influenza infection rates.[28] Extreme air pollution levels are known to increase near-term mortality.[29,30] There is also evidence that fluctuations around normal levels can modestly increase all-cause mortality for the elderly.[31] The effect of daily fluctuations, generally within normal levels, on mortality from respiratory disease is hard to study because there is no general source of daily mortality by cause of death at a local geographic level. Studying COVID-19, for which daily mortality data is available, provides a window into what could be a broader link between air pollution rates, within normal levels, and mortality from respiratory and related causes.

For most COVID-19 decedents, death is preceded by hospitalization and often an ICU stay. The average hospital stay for COVID-19 prior to death is 7 days.[24] Also, patients who are ill but not yet hospitalized are likely to spend little time outdoors. This raises the question of the mechanism through which outdoor pollution levels influence mortality over the next several weeks, since indoor pollution levels are likely to be lower than outdoor levels. However, indoor and outdoor air pollution are known to be highly correlated, including in hospitals.[32-34] Thus, it is plausible that indoor exposure to pollution is an important contributor to death. This suggests hospitals should pay greater attention to air quality for patients with COVID-19.

Limitations

We acknowledge several limitations to our analysis. First, we rely on observational data. But we are unable to hypothesize plausible factors that would not be captured by the county and day fixed effects, but would be correlated with both AOD and infection rates, and thus could produce omitted variable bias. We note that we find similar effect magnitudes in urban and rural counties, and in the Eastern versus Western U.S., suggesting that the association is robust to the differences in COVID mortality seen among states and between urban and rural areas. Moreover, experimental studies of the association between air pollution and COVID-19 mortality are infeasible.

Second, our measure of air pollution levels (AOD) is based on satellite remote sensing measurement. The AOD measure provides much better geographical and temporal coverage, especially in rural areas, than the alternative of ground-based air quality monitor data (see Appendix section 5), but has important limitations. First, satellites cannot measure AOD in areas with heavy cloud coverage or bright surfaces. We address this limitation through interpolation for days with missing AOD, and provide evidence that results are not sensitive to the specific interpolation strategy used. Second, we cannot identify the contributions of specific pollutants, since AOD measures only overall aerosol levels. Third, AOD measures aerosol for the whole vertical column of atmosphere. However, AOD measures are strongly correlated with ground-based measures.[18,20] Moreover, imprecision in the measure would tend to bias the observed association toward zero.

We control for lagged COVID-19 infections; actual infections are known to be a multiple of confirmed infections, with the multiple being especially high early in the pandemic due to limited test availability and more generally varying over both time and geography.[35] However, lagged infections are likely to be a good measure of symptomatic infections, since people with symptomatic infection are more likely to be tested. Also, our infection measure strongly predicts mortality, as expected. Finally, our results for AOD are robust to whether we control for lagged infections and to the duration of our lag period.

We study only deaths attributed to COVID-19 in death records, but excess mortality from other causes is also high during periods with high COVID mortality (see https://www.cdc.gov/nchs/nvss/vsrr/covid19/excess_deaths.htm). Thus, our study may underestimate the full effect of air pollution fluctuations on COVID-related mortality.

Conclusion

We report evidence that daily fluctuations in local air pollution predict higher COVID-19 mortality over the next 3 weeks, in both urban and rural areas, and in both the Eastern and Western U.S. The magnitudes are modest, but nonetheless important given the large scale of COVID-related mortality. Our results suggest the need for attention to both reducing outdoor air pollution and, in the near term, improving indoor air filtration and ventilation, especially in hospitals.

Table 1: Summary Statistics

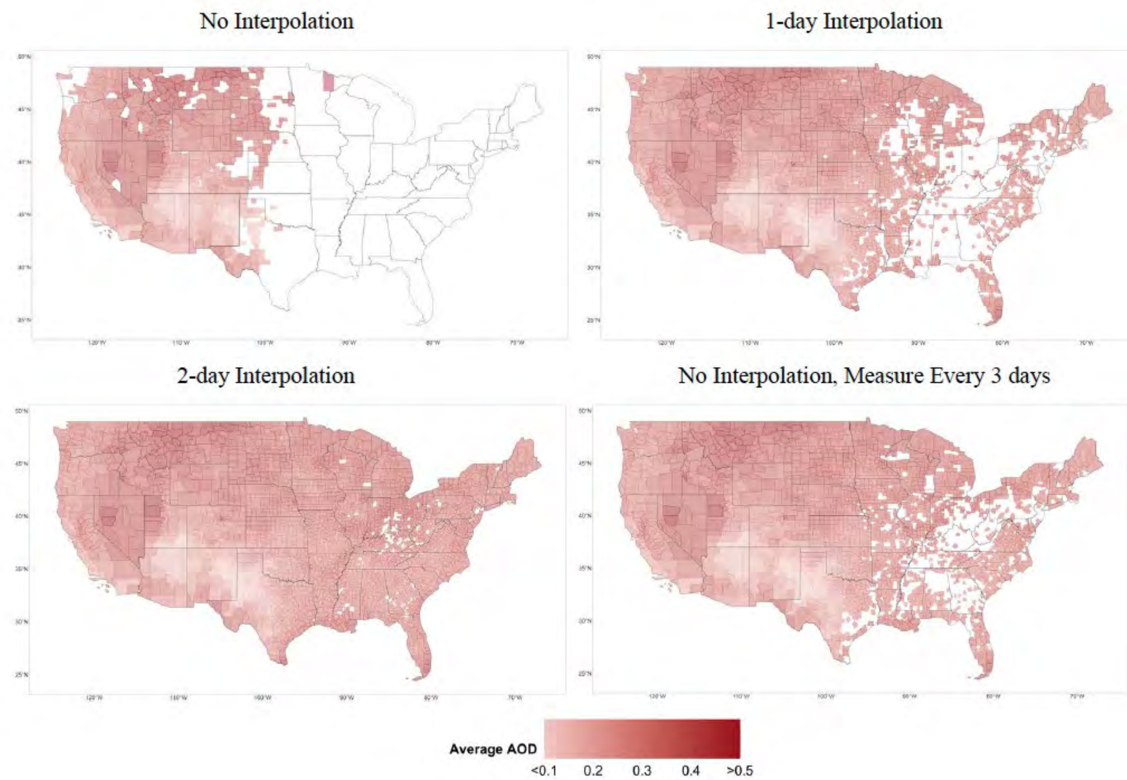
Data are daily county means, with counties weighted equally. Standard deviations are in parentheses. Sample size is number of counties (or county*days) in dataset with complete aerosol data for days -28 (28 days before measuring mortality) through day -1 (day before date for measuring mortality). Mortality and COVID-19 cases are 7-day moving averages. Sample period is March 1, 2020 through August 26, 2021**.** Last two columns: Aerosol data is interpolated for one or two missing daily values using data for the days before and after the missing day or days. Vaccination rate is assumed to be zero prior to first day with positive value in each county.

Variable	**Full Dataset**	$n = 28$ **lags**	$n = 28$ **lags**	$n = 28$ **lags**	$n =$ **every 3 days of 28 lags**
AOD Interpolation Approach	Not applicable	Require data on all 28 preceding days	Interpolate for single missing day	Interpolate for up to two adjacent days	Require data every 3rd day during preceding 28 days
No. of Counties	3,103	491	1,772	2,942	2,176
County × Day Observations	859,001	24,583	111,987	256,348	76,035
COVID-19 Mortality	0.377 (2.34)	1.06 (4.36)	0.72(5.41)	0.51 (3.87)	0.69 (4.59)
COVID-19 Mortality/100k people	0.396 (1.110)	0.234 (0.584)	0.271 (0.889)	0.310 (1.006)	0.275 (0.922)
COVID-19 Cases	24.4 (149.4)	75.8 (322.1)	46.9 (349.7)	34.52 (253.0)	48.3 (318.3)
COVID-19 Cases/100k people	22.70 (32.71)	15.76 (24.11)	18.53 (29.80)	20.42(31.23)	18.90 (30.45)
Aerosol optical depth (AOD, unitless)	0.290 (0.336)	0.311(0.409)	0.338(0.438)	0.327 (0.395)	0.339 (0.443)
Vaccination Rate (%)	29.54 (17.34)	36.96 (15.78)	32.34 (17.25)	30.95 (17.91)	33.79 (16.93)
Daily Precipitation (mm)	1.73 (5.84)	0.348 (1.585)	0.971 (3.788)	1.75 (5.75)	1.137 (4.375)
Daily Temperature (Celsius)	16.5 (8.82)	20.574 (6.081)	19.381 (7.061)	18.6 (7.71)	18.970 (7.256)
County population (2020 data)	114,936 (392,295)	449,095 (1,263,128)	223,002 (820,129)	157,559 (610,502)	247,692 (890,658)

Figure 1: Data Visualization

Panel A. AOD Data Coverage, $n = 28$

Map shows number of counties in sample (for at least one day in sample period) with no interpolation, one-day interpolation, two-day interpolation, or with AOD measured only every 3 days. Color gradient shows average AOD by county over our sample period (2020-03-01 to 2021-08-26).



Panel B. National Average Time Trends of AOD (without interpolation)

Note: The range of county-level AOD in our data is from -0.065 to +6.06, with a mean of 0.294. The spike in September 2020 and July 2021 are coincident with large wildfires in CA: the August Complex in August 2020, 1,032,648 acres; and the Dixie fire in July 2021, 963,276 acres.

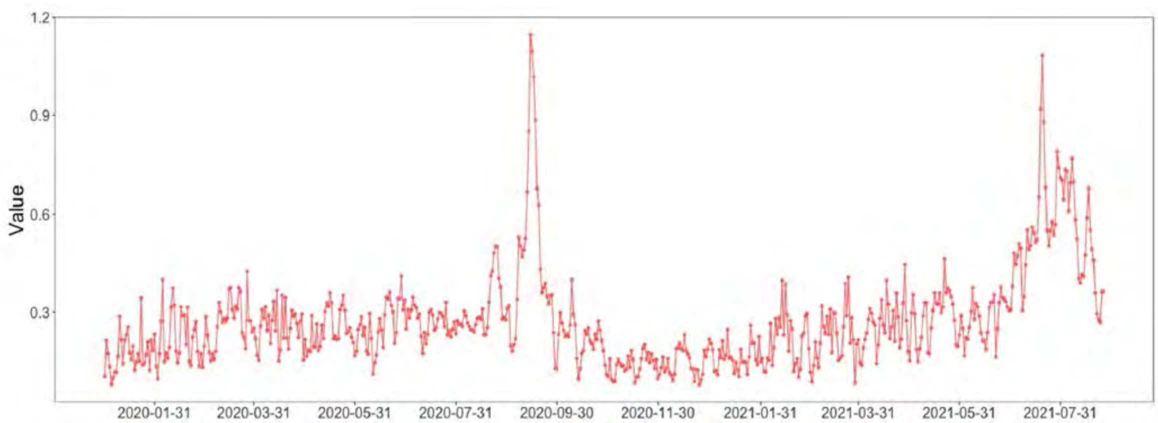
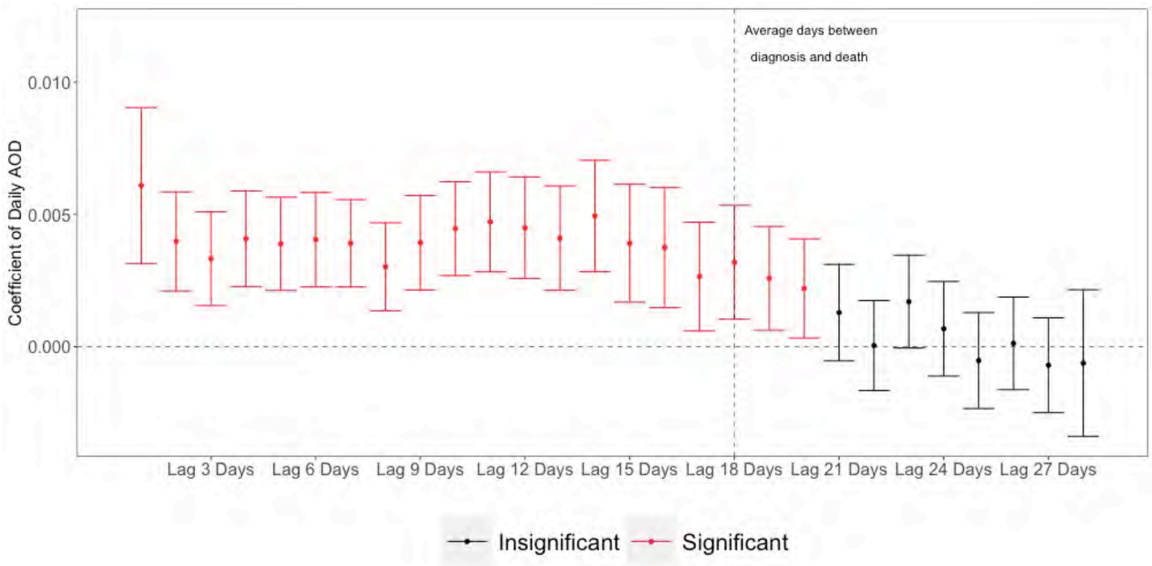


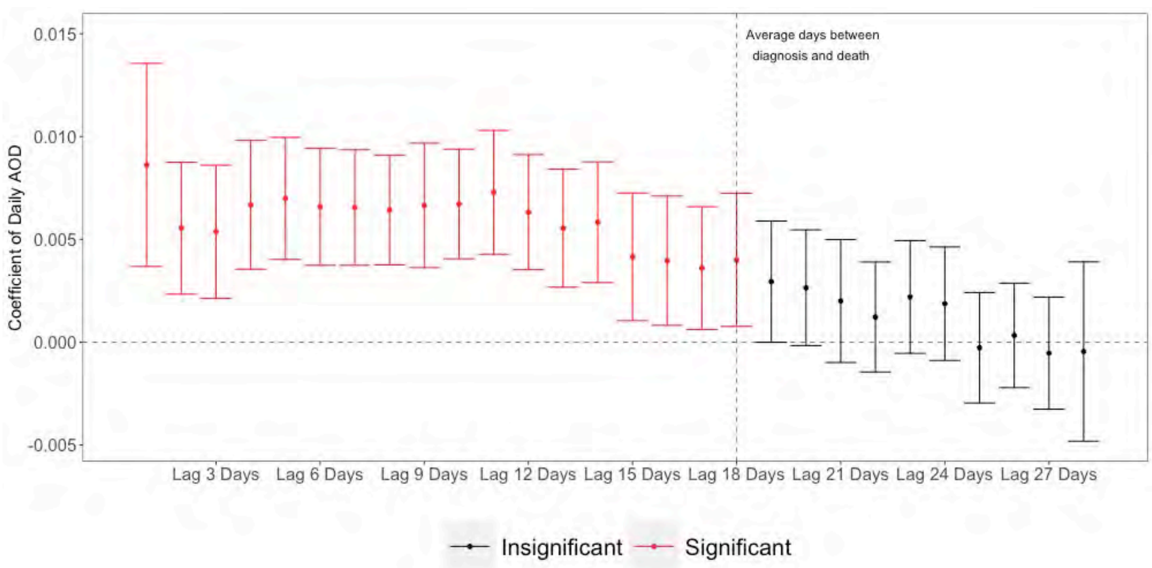
Figure 2: Correlation between Lagged Daily Air Pollution and COVID-19 Mortality

Note: Regressions using county and date fixed effects and indicated interpolation. Outcome variable is log(7-day moving average deaths + 1). Covariates are: "COVID-19 Cases" is 7-day moving average of new cases lagged 18 days; "Vaccination Rate" is percentage of fully vaccinated population in each county lagged 18 days; "Temperature" and "Precipitation" are averaged across past two weeks for each county. Standard errors are clustered at county-level. Vertical bars show 95% confidence intervals.

Panel A. Using 2-day interpolation of AOD



Panel B. Using 1-day interpolation of AOD



Panel C. No interpolation but measuring lagged AOD only every three days

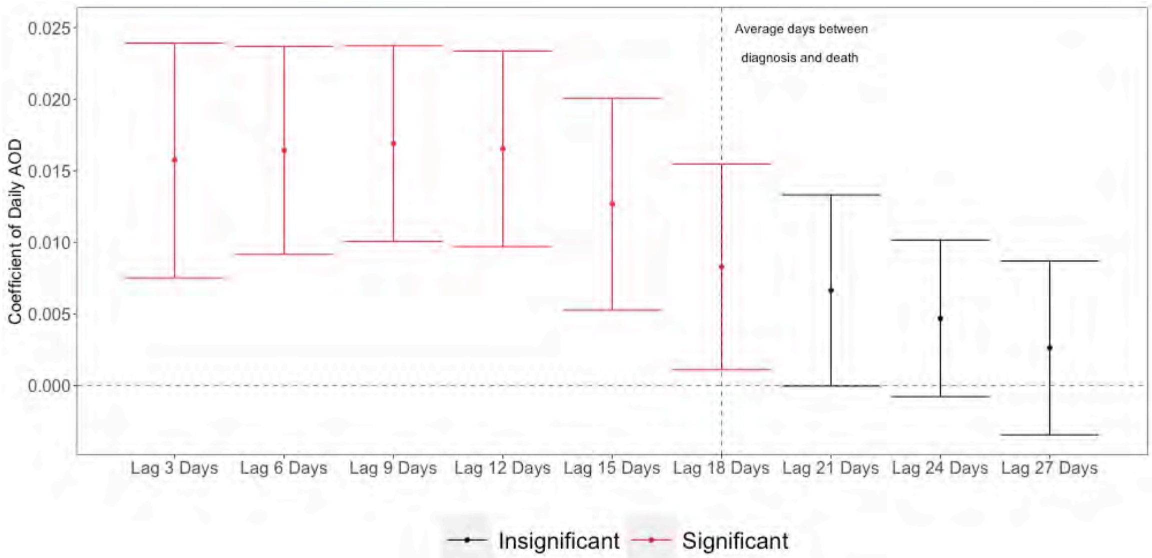
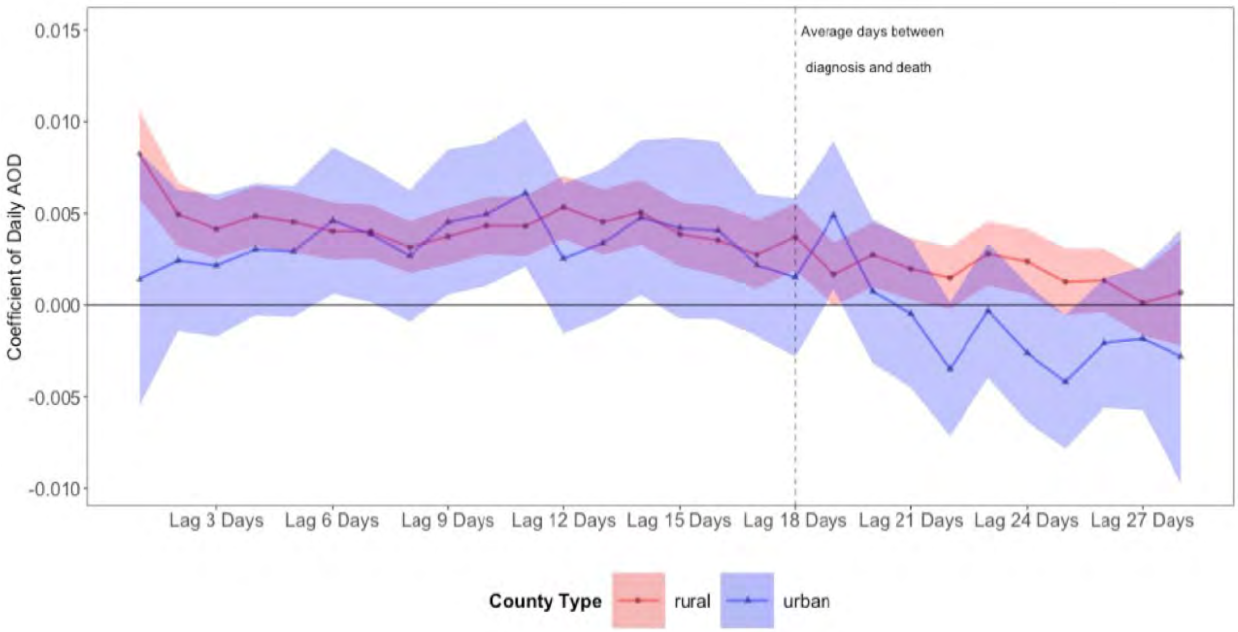


Figure 3: Lagged Air Pollution and COVID-19 Mortality: Urban vs. Rural Counties; West vs. East

Note: Regressions are similar to Figure 2, Panel A, and use 2-day interpolation. **Panel A**. Sample is divided into urban (counties within a Combined Statistical Area, 1,088 counties) vs. rural (remaining 1,854 counties). **Panel B**. Sample is divided into Western U.S. (counties within a western state (1,060 counties in *WA, OR, CA, ID, NV, UT, AZ, MT, WY, CO, NM, ND, SD, NE, KS, OK, TX,*) vs. Eastern U.S. (remaining 1,882 counties). Shaded areas show 95% confidence intervals.

Panel A. Urban vs. Rural Mortality



Panel B. Mortality in Western vs. Eastern U.S.

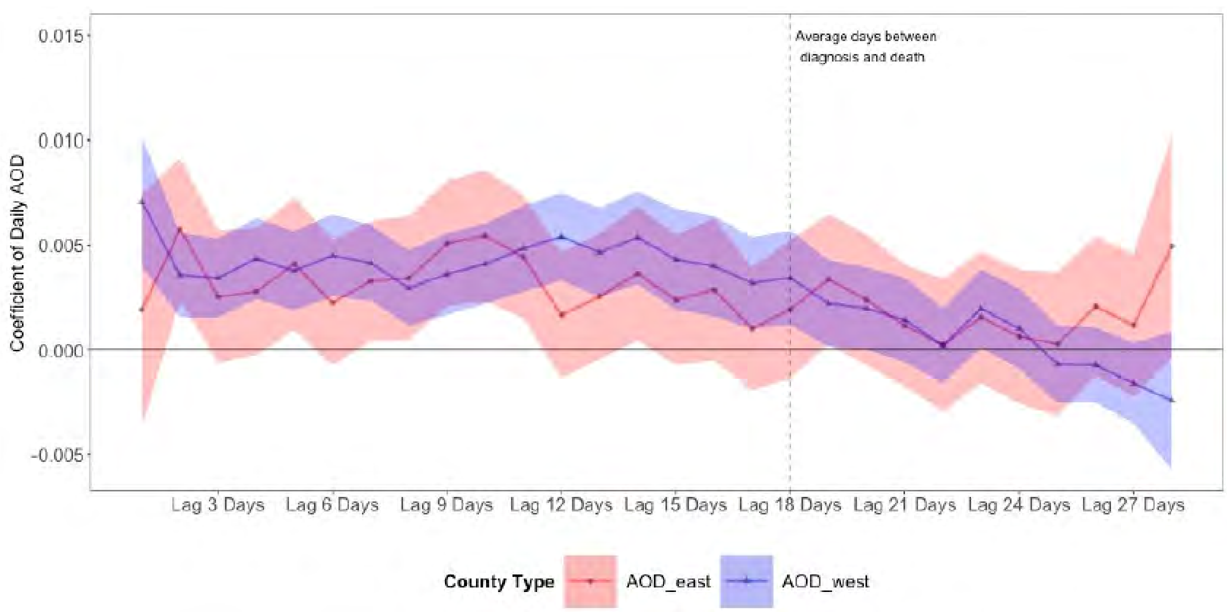


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Table 2: Regression Analysis of Relationship between Short-term Air Pollution Exposure and COVID-19 Mortality

Note: Regressions, with county and date fixed effects, of COVID mortality (log(7-day moving average deaths + 1) on High Pollution Exposure and covariates. High Pollution Exposure is the fraction of "high pollution days" in the past 21 days (for regressions using daily AOD data) or days 3, 6, 9, 12, 15, 18 and 21 (for regressions using AOD measured every 3 days). High pollution days are defined as days when county AOD (with indicated interpolation) exceeds the median of same-day AODs across all counties. Covariates are same as in Figure 2. Standard errors are clustered at the county level. *, **, *** indicates statistical significance at the 10%, 5%, and 1% level, respectively. Significant results, at 5% level or better, in **boldface**.

	Outcome: Log(COVID-19 Death + 1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Interpolation	2-day	1-day	None	2-day	1-day	None
AOD Measures	Daily	Daily	Every 3 days	Daily	Daily	Every 3 days
High Pollution	**0.0437*** **	**0.0563*** **	**0.0306*** **	**0.0509*** **	**0.0632*** **	**0.0333*** **
Exposure	**(0.0119)**	**(0.0164)**	**(0.0097)**	**(0.0119)**	**(0.0167)**	**(0.0096)**
COVID-19 Cases (lag	**0.0004*** **	**0.0003*** **	**0.0003*** **	**0.0004*** **	**0.0003*** **	**0.0003*** **
18 days)	**(0.0001)**	**(0.0001)**	**(0.0001)**	**(0.0001)**	**(0.0001)**	**(0.0001)**
Vaccination Rate (lag				**-0.0028*** **	**-0.0030*** **	**-0.0032*** **
18 days)				**(0.0004)**	**(0.0006)**	**(0.0006)**
Precipitation, lag 2				**-0.0019** **	-0.0004	-0.0017
week average				**(0.0008)**	(0.0015)	(0.0012)
Temperature, lag 2				0.0010	0.0016	0.0018
week, average				(0.0014)	(0.0019)	(0.0018)
County and date FE	Y	Y	Y	Y	Y	Y
Observations	344,920	155,545	110,256	344,920	155,545	110,256
R^2	0.7674	0.8182	0.8168	0.7693	0.8199	0.8168
Within R^2	0.0837	0.0879	0.0861	0.0910	0.0962	0.0953

References:

1. Neupane B, Jerrett M, Burnett RT, Marrie T, Arain A, Loeb M. Long-term exposure to ambient air pollution and risk of hospitalization with community-acquired pneumonia in older adults. *American Journal of Respiratory and Critical Care Medicine* 2009;181:47-53.
2. Guarnieri M, Balmes JR. Outdoor air pollution and asthma, *Lancet* 2014;383:1581-1592.
3. Clay K, Lewis J, Severnini E. Pollution, infectious disease, and mortality: evidence from the 1918 Spanish influenza pandemic. *Journal of Economic History* 2018;78(4):1179-1209.
4. Liu YM, Ao CK. Effect of Air pollution on health care expenditure: evidence from respiratory diseases. Health Economics 2021;30:858-875.
5. Ogen Y. Assessing nitrogen dioxide (NO2) levels as a contributing factor to coronavirus (COVID-19) fatality. Sci. Total Environ. 2020;726:138605.
6. Fattorini D, Regoli F. Role of the chronic air pollution levels in the Covid-19 outbreak risk in Italy. Environmental Pollution 2020;264:114732.
7. Hendryx M, Luo J. COVID-19 Prevalence and fatality rates in association with pollution emission concentrations and emission sources. Environmental Pollution 2020;265:115126.
8. Wu X, Nethery RC, Sabth MB, Braun D, Dominici F. Air pollution and COVID-19 mortality in the United States: strengths and limitations of an ecological regression analysis. Science Advances 2020;6:eabd4049.
9. Liang D, Shi L, Zhao J, Liu P, Sarnat JA, Gao S, Schwartz J, Liu Y, Ebelt ST, Scovronick N, Chang HH. Urban air pollution may enhance COVID-19 case-fatality and mortality rates in the United States. The Innovation 2020;1:100047.
10. Konstantinoudis G, Padellini T, Bennett JE, Davies B, Ezzati M, Blangiardo M. Long-term exposure to air-pollution and COVID-19 mortality in England: a hierarchical spatial analysis. Environment International 2021;146:106316.
11. Travaglio M, Yu Y, Popovic R, Selley L, Leal NS, Martins LM. Links between air pollution and COVID-19 in England. Environmental Pollution 2021;268:115859.
12. Pansini R, Fornacca D. Early spread of COVID-19 in the air-polluted regions of eight severely affected countries. Atmosphere 2021;12(6):795.
13. Isphording IE, Pestel N. Pandemic meets pollution: Poor air quality increases deaths by COVID-19. Journal of Environmental Economics and Management 2021;108:102448.
14. Pegoraro V, Heiman F, Levante A, Urbinati D, Peduto I. An Italian individual-level data study investigating on the association between air pollution exposure and Covid-19 severity in primary-care setting. BMJ Public Health 2021;21:902.
15. Adhikari A, Yin J. Short-term effects of ambient Ozone, PM2.5, and meteorological factors on COVID-19 confirmed cases and deaths in Queens, New York. Int. J. Environ. Res. Publ. Health 2020;17:4047.

16. Bashir MF., Ma BJ, Bilal, Komal B, Bashir MA, Farooq TH, Iqbal N, Bashir M. Correlation between environmental pollution indicators and COVID-19 pandemic: a brief study in Californian context. Environ Res. 2020;187:109652.

17. Singh T, Ravindra K, Sreekanth V, Gupta P, Sembhi H, Tripathi SN, Mor S. Climatological trends in satellite-derived aerosol optical depth over North India and its relationship with crop residue burning: rural-urban contrast. Sci. Total Environ. 2020;748:140963.

18. Liu Y, Park RJ, Jacob DJ, Li Q, Kilaru V, Sarnat JA. Mapping annual mean ground-level PM2.5 concentrations using multiangle imaging spectroradiometer aerosol optical thickness over the contiguous United States. Journal of Geophysical Research 2004;109(D12):D22206.

19. van Donkelaar AV, Martin RV, Brauer M, Hsu NC, Kahn RA, Levy RC, Lyapustin A, Sayer AM, Winker DM. Global estimates of fine particulate matter using a combined geophysical-statistical method with information from satellites, models, and monitors. Environmental Science and Technology 2016;50:3762-3772.

20. Zhang R, Li H, Khanna N. Ejustice and the COVID-19 pandemic: evidence from New York State. Journal of Environmental Economics and Management 2021;110:102554.

21. Daniels MJ, Dominici F, Samet JM, Zeger SL. Estimating particulate matter-mortality dose-response curves and threshold levels: an analysis of daily time-series for the 20 largest U.S. cities. American Journal of Epidemiology 2000;152(5):397-406.

22. Schwartz J, Laden F, Zanobetti A. The concentration-response relation between PM2.5 and daily deaths. Environmental Health Perspective 2002;110(10):1025-1029.

23. McLaughlin JM, Khan F, Pugh S, Swerdlow DL, Jodar L. County-level vaccination coverage and rates of COVID-19 cases and deaths in the United States. SSRN Working Paper 2021; http://ssrn.com/abstrct=3908476.

24. Yang X, Yu Y, Xu J, et al. Clinical course and outcomes of Critically Ill patients with SARS-CoV-2 pneumonia in Wuhan, China: a single-centered, retrospective, observational study. Lancet Respir. Med. 2020;8:475–481.

25. Marschner IC. Estimating age-specific COVID-19 fatality risk and time to death by comparing population diagnosis and death patterns: Australian data, BMC Medical Research Methodology 2021;21:126.

26. Kurt OK, Zhang J, Pinkerton KE. Pulmonary health effect of air pollution, Current Opinion in Pulmonary Medicine 2017;22(2): 138-143.

27. Horne BD, Joy EA, Hofmann MG, Gesteland PH, Cannon JB, Lefler JS, Blagev DP, Korgenski EK, Torosyan N, Hansen GI, Kartchner D, Pope-III CA. Short-term elevation of fine particulate matter air pollution and acute lower respiratory infection. American Journal of Respiratory and Critical Care Medicine 2018;198(6):759-766.

28. Croft DP, Zhang W, Lin S, et al. The association between respiratory infection and air pollution in the setting of air quality policy and economic change. Annuals of the American Thoracic Society 2019;16(3):321-330.

29. Xi Y, Kshirsagar AV, Wade TJ, Richardson DB, Brookhart MA, Wyatt L, Rappold AG. Mortality in U.S. hemodialysis patients following exposure to wildfire smoke. Clinical Epidemiology 2020;31(8):1824-1835.

30. Chen G, Guo Y, Yue F, et al. Mortality risk attributable to wildfire-related PM2.5 pollution: a global time series study in 749 locations. Lancet Planetary Health 2021;5:e579-e587

31. Di Q, Dai L, Wang Y, Zanobetti A, Choirat C, Schwartz JD, Dominici F. Association of short-term exposure to air pollution with mortality in older adults. Journal of the American Medical Association 2017;318(24):2446-2456.

32. Scheepers PTJ, Wel LV, Beckmann G, Anzion RBM. Chemical characterization of the indoor air quality of a university hospital: penetration of outdoor air pollution. International Journal of Environmental Research and Public Health 2017;14:497.

33. Chamseddine A, Alameddine I, Hatzopoulou M, El-Fadel M. Seasonal variation of air quality in hospitals with indoor–outdoor correlations. Building and Environment 2019;148:689-700.

34. Lee HJ, Lee KH, Kim DK. Evaluation and comparison of the indoor air quality in different areas of the hospital. Medicine 2020;99(52):e23942.

35. Pei S, Yamana TK, Kandula S, Galanti M, Shamann J. Burden and characteristics of COVID-19 in the United State during 2020. Nature 2021;598:338-341.