$PM_{2.5}$ and ozone air pollution levels have not dropped consistently across the US following societal covid response

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Significance

The widespread and rapid social and economic changes from covid response might be expected to dramatically improve air quality across the US. However, a large, US national database from the US Environmental Protection Agency of almost 500 regulatory monitors each for fine particulate matter ($PM_{2.5}$) and ozone does not support that expectation. Year-2020 average $PM_{2.5}$ concentrations are slightly higher than expected, based on long-term and seasonal trends; ozone concentrations are lower than expected, but not consistently across the US and the anomaly size has decreased since the first stay-at-home order. Our findings show that the enormous changes from the covid response have not lowered $PM_{2.5}$ levels across the US beyond their normal range of variability.

Abstract

Analysis of a large national dataset of fine particulate matter ($PM_{2.5}$) and ozone air pollution from the US Environmental Protection Agency indicate opposing differences in average concentrations during the covid response period, relative to expected levels. These are the two most important pollutants in terms of public health impacts and non-attainment in the US. Post- covid response, average $PM_{2.5}$ levels are modestly higher (~10%) than expected; average ozone levels are lower (~7%). However, the size of the post-response ozone anomaly is decreasing with time. In addition, no individual US state had lower-than-expected $PM_{2.5}$ for all weeks post- covid response, and only one US state (California) met that criteria for ozone. Two non-covid factors, meteorology and regional transport, do not fully explain observed trends. These findings are unexpected given the large reduction in many household's activities associated with "stay at home" and other covid responses. We hypothesize that this result partly arises from the fact that ozone and the majority of $PM_{2.5}$ are secondary pollutants formed in the atmosphere from emissions from many sources (i.e., not just traffic). Preliminary analysis of nitrogen dioxide (NO_2) data in a few cities reveals substantially lower-than-expected (~31%) concentrations post-covid. NO_2 is a primary pollutant and is much more strongly associated with traffic than $PM_{2.5}$ or ozone.

1. Introduction

With the enormous and extremely rapid social and economic changes happening because of the novel coronavirus disease of 2019 ("covid"), including stay-at-home orders enacted in nearly all US states, there is interest in quantifying the air pollution impacts of those orders. Changes in air pollution post-covid could reveal, for example, how macroscopic changes in the economy affect air quality, and how those changes differ throughout the US. More broadly, responses to covid create a unique opportunity to quantify the effect of human activity on air quality. This general approach has been done multiple times at a more limited scale -- for example, studying impacts of sudden industrial closure (e.g., a steel mill in Utah Valley[1]; copper smelters throughout the US[2]), widespread power outage in the Northeastern US[3], new regulation such as a coal ban in Dublin[4] and a congestion charging scheme in London[5], and the 1996 Atlanta[6,7] and 2008 Beijing Olympics[8,9]. However, changes attributable to the covid response are unprecedented in size, scope, and speed.

Understanding the changes in air pollution attributable to stay-at-home orders and other covid responses is not as straightforward as simply looking before versus after those orders, or comparing a day this year to the same day last year, for several reasons. Air pollution concentrations at a given location vary on time scales from seconds to years, in ways that are random (or quasi-random) and systematic (i.e., non-random). Temporal variability is caused by changes in emissions and meteorology, which can impact factors such as rates of transport, production, removal, and dilution. Examples include a shift in wind direction so that a location is no longer downwind of a large emission source; chemical reaction rates and atmospheric mixing increasing as temperatures become warmer from nighttime to daytime, or from winter to spring to summer; and emission rates changing year-to-year because of regulations and changes in economic activity. The net result is that because of random and systematic temporal variability, concentrations post-covid may be different than pre-covid (e.g., one month or one year earlier) for reasons unrelated to covid.

Our paper adds to the literature on changes in air pollution concentration associated with specific causes, including studies of the emissions, air pollution, or health benefits from environmental regulation ("accountability studies"). That literature addresses the random and systematic variability in pollution concentrations mentioned above via, e.g., detrending and counterfactual emissions scenarios (1-11).

Our paper also adds to the existing literature exploring covid-related impacts on air pollution and related activity levels (12-18). Much of the news in the popular press regarding impacts of covid on air pollution emphasizes that concentrations have improved post-covid (19-24); our investigation aims to test those claims using a national dataset of in-situ concentration measurements.

This paper uses nationwide, publicly-available US EPA monitoring data to investigate changes in air quality across the entire US to widespread covid response measures. The methods and comparisons we employ control for random and systematic variability on multiple time scales. The EPA data represent the largest data source of publicly-available, accessible, and robust measurements of air pollution concentrations for the US. We investigate conditions by state and nationally, for the two pollutants EPA has made available online for March and April 2020: fine particulate matter ($PM_{2.5}$) and ozone. We close by comparing against a third pollutant, NO_2, using limited data for three cities obtained from a non-EPA website. To our knowledge, no peer reviewed articles have systematically analyzed the changes in measured ozone and $PM_{2.5}$ air pollution concentrations in the US to the covid response.

2. Methods

2.1 General approach

We employ publicly-available daily-average concentrations of air pollution measured at US EPA monitors. We downloaded data from the US EPA AirData website (https://www.epa.gov/outdoor-air-quality-data/download-daily-data) on May 2, 2020. As of May 4, 2020, data for two pollutants are available from the US EPA for the time-period of interest for covid (March 2020 and later): fine particulate matter ($PM_{2.5}$, i.e., particles smaller than 2.5 μm) and ozone. These are the two most important pollutants in the US in terms of human health impacts and non-attainment (more than 100 million Americans live in areas that violate the National Ambient Air Quality Standards for one of these pollutants).

We downloaded and analyzed all ambient monitoring data available on the EPA website, i.e., all available measurements, pre- and post-covid, for both pollutants. A strength of this analysis is the national scope of the dataset, which contains air quality measurements across the entire US. In addition, we separately obtained limited data for three cities on the Air Quality Index (AQI) for a third pollutant, nitrogen dioxide (NO_2), from a private (non-EPA) website; these are the raw AQI values "scraped" from EPA websites.

We use "pre-covid" and "post-covid" as general terms: "pre-covid" refers to weeks-of-the-year when, in year-2020, the novel coronavirus disease of 2019 had little or no impact on activities in the US; "post-covid" refers to weeks-of-the-year when, in 2020, activities in the US were noticeably impacted by covid. The term "stay at home" refers to a specific requirement (also called "shelter in place") announced by most state governments; these orders have a specific, declared start date (Table S1).

2.2 Comparison metric: temporally-corrected "robust differences" ("D")

Our comparison metric for each individual monitoring site is the weekly median concentration for 2020, relative to the temporally-corrected historical median, normalized to the interquartile range (IQR):

$$D_i = (C_{2020,i} - C_{h,i})/I_{h,i} \quad . \qquad \text{Eq. 1}$$

Eq. 1 is calculated for each week ("i") and for each monitor. D_i is the comparison metric for week i, $C_{2020,i}$ is the weekly-median concentration (i.e., the median of 7 daily-average concentrations) for week i during year-2020, $C_{h,i}$ is the temporally-corrected historical median concentration for week i plus/minus 2 weeks, and $I_{h,i}$ is the interquartile range (IQR, 75th percentile minus 25th percentile) for week i plus/minus 2 weeks. For example, to calculate $C_{h,i}$ and $I_{h,i}$ for week 10, we use historical (2010-2019) data for weeks 8-12. The "plus/minus 2 weeks" approach for historical data increases the sample size for the comparisons, gives a broader historical comparison than just one week, and helps smooth atypical weeks in the historical dataset.

"D" (in Eq 1) is sometimes called "robust difference": "robust" because it is based on median and IQR rather than mean and standard deviation, so it is not impacted by outliers. D=0 indicates that the year-2020 median is equal to the "expected" value (i.e., the temporally-corrected long-term average median). D=1 indicates that the year-2020 value is one IQR above the expected value; D=-2 indicates two IQRs below the expected value.

Temporal correction is needed because concentrations exhibit systematic long-term (10-year) trends that can vary by location. The temporal correction for a monitor on week i is the 10-year slope of weekly-median historical concentrations at that monitor (see example plots in Fig. S1). In this manner, we compare to the "expected" concentration for week i in year-2020, accounting for long-term (10-year) trends for that week-of-year at that location. We use a 10-year timeframe because shorter-duration analyses (e.g., 3 years or 5 year) can be overly influenced by outlier years. The interquartile range ($I_{h,i}$) is calculated using the prior 3 years of data (2017-2019); we employ this metric as a relatively recent measure of the typical spread in the data.

The overall median (IQR) temporal correction among all monitors is -0.20 (-0.05 to -0.39) μg m^{-3} per year for $PM_{2.5}$ and -0.06 (-0.3 to +0.3) ppb per year for ozone; the median (IQR) R^2 value for the best-fit lines is 0.36 (0.09 - 0.57). Dividing the median slope by the median concentrations given below (10 μg m^{-3}; 50 ppb), those slopes represent a typical annual change of -2% (i.e., a 2% reduction; IQR: -0.6% to -4%) for $PM_{2.5}$ and -0.1% (-0.6% to +0.6%) for ozone. For $PM_{2.5}$, approximately half (53%; n= 250) of the monitors have a negative slope for all 17 weeks and a small number (2%; n=9) have positive slope for all 17 weeks; for ozone, 11% (n=52) of slopes are strictly positive and 15% (n=71) are strictly negative.

We calculate D for each monitor-week in the target window. This analysis reveals whether year-2020 concentrations are higher- or lower-than expected, for pre- and post-covid weeks, but does not elucidate their cause. If year-2020 concentrations happened to be higher- or lower-than-expected prior to covid (e.g., because of atypical meteorology, or if pre-covid changes in the economy impacted emissions), we should see those impacts in the results for the pre-covid weeks.

2.3 Data acquisition and selection

We start by downloading all data (daily average concentrations, December 15, 2009 - April 28, 2020) for all monitors with one or more days of data in year-2020. We restricted the analysis to consider a specific window of days each year: for 2020, the window is January 1 - April 28 (119 days); for years 2010-2019, the window is December 17 - May 12 (total: 147 days), i.e., the year-2020 range plus/minus 2 additional weeks. (As described above, the "D" metric compares a week during 2020 against that historical week plus/minus two weeks.) All data outside of these windows were not considered in the analysis.

April 28, 2020 (the last date of analysis) is the 119th day of 2020, and the completion of the 17th week of the year; thus, analyses by week extend through week 17. (2020 is a leap year; that aspect does not directly impact analyses here, which are based on day-of-year and week-of-year.) Weeks are sequential: week 1 is days 1-7 of the year, week 2 is days 8-14 of the year, etc.

We carefully examined the completeness of data from each year and monitoring site to determine whether it would be included in the study. As described next, these checks are performed as a two-step process applied separately to each monitor.

First, we tested each monitor-year for data sufficiency. For years 2010-2019, if any monitor-year contains less than 75% of the expected number of days in the target window (75%×147=111 days), then that year of data for that monitor is excluded. For year-2020, we checked the number of days of data pre-covid (January 1 - March 18; 93 days) and post-covid (March 19 - April 28; 42 days); if either period's data contains less than 75% of the expected days (75%×78 days= 59 days; 75%×47 days= 36 days), then that monitor is excluded from the analysis.

Second, we ensure that a monitor has a sufficient number of years of valid data. This step employs the following three data requirements (see also Fig. S2): (1) Monitors with fewer than 3 years of data are excluded. (2) Monitors without at least two of the last three years of data are excluded (this requirement is to increase robustness of the IQR, which is calculated using available data from the past 3 years). (3) (i) For monitors with 8 or more years of data for 2010-2019, we calculate the 10-year slope from that monitor's available data. (ii) For monitors with less than 8 years of data for 2010-2019, we determined if there are one or more monitors within 50 km. If there are, then we impute a slope using inverse distance weighting (IDW) of the slopes from up to 4 closest monitors within 50 km. If there are no other monitors within 50 km, then we exclude that monitor from the analysis. This last rule is designed to increase robustness of the temporal correction factor (temporal slope using available data from 2010-2019).

The US EPA AirData website provided daily-average concentrations for 842 monitors for $PM_{2.5}$ and 1161 monitors for ozone. Our data completeness algorithm excluded a total of 370 monitors (44%) for $PM_{2.5}$ and 693 monitors (58%) for ozone because of insufficient data. Therefore, the results and discussion are based on data from 472 $PM_{2.5}$ and 468 ozone monitors. Each monitor is in a different location. No $PM_{2.5}$ monitors in West Virginia, and no ozone monitors in Rhode Island, Hawaii, Mississippi and West Virginia met the completeness criteria. State-specific results refer to states with monitors that met the inclusion criteria.

3. Results

3.1 Particulate matter and ozone concentrations post-covid

We use the temporally-corrected historical median as the "expected" value (see Methods). As described next (see Figs. 1, 2, 3, and 4), overall we observe that concentrations post-covid are lower-than-expected for ozone and slightly higher-than-expected for $PM_{2.5}$. The size of the ozone anomaly was largest one week before the earliest stay-at-home order; it has since then been shrinking (returning to expected concentrations). NO_2 data for three cities (see Fig. 5) suggest that NO_2 concentrations are much lower-than-expected based on the historical range for this time of year. Those results raise the obvious question as to which changes are covid-related (i.e., caused by changes in societal and economic activity occurring in response to covid) and which are not; however, results here cannot ascribe causality.

Fig. 1 presents two analyses on whether year-2020 concentrations are different than expected, using 2010-2019 data as the comparison. In Fig. 1, post-covid average $PM_{2.5}$ concentrations are towards the high end of the historical range, indicating, on average, a modest (~10%) increase relative to expected concentrations. In contrast, post-covid average ozone concentrations are lower (~7%) than expected, with the largest drop occurring during weeks 11-12 (i.e., March 12-25, 2020); average concentrations afterwards are still less-than-expected but by a smaller amount.

Historical $PM_{2.5}$ concentrations are lower with temporal correction than without it (Fig. 1, right) because $PM_{2.5}$ concentrations are generally decreasing each year (~2%/y, on average). Therefore, a direct (uncorrected) comparison of year-2020 concentrations to the long term average would incorrectly suggest that $PM_{2.5}$ concentrations are lower than expected. In contrast, temporally corrected results, that account for the long term trend, in Fig. 1 suggest that $PM_{2.5}$ concentrations post-covid are similar to, or are slightly higher than, expected concentrations.

For ozone, the temporal correction is minor (~0.1% per year); the data exhibit year-to-year variability but without a strong 10-year trend. Seasonally, ozone concentrations generally increase during January to April, reflecting increasing photochemical activity. Therefore, a direct comparison of weeks post- vs pre-covid would incorrectly suggest that ozone concentrations are higher than expected; that conclusion fails to account for ozone's seasonal trend.

We can more precisely quantify the above differences by considering "pre-covid" as the average during weeks 1-10 and "post-covid" as the average during weeks 11-17, based on values in Fig. 1. "Expected concentrations" refer to the temporally-corrected historical medians; here, they are the pre-covid and post-covid mean of those weekly medians. We find that actual year-2020 $PM_{2.5}$ concentrations (units: $\mu g/m^3$) are 6.68 pre-covid and 5.95 post-covid, compared to expected concentrations of 6.28 pre-covid and 5.41 post-covid; D values (unitless) are 0.10 pre-covid, 0.18 post-covid. Those values indicate that post-covid year-2020 $PM_{2.5}$ concentrations are 0.54 $\mu g/m^3$ (10%) higher than expected (i.e., a post-covid comparison of actual versus expected), and are 0.73 $\mu g/m^3$ (11%) lower than pre-covid (i.e., comparison of actual concentrations pre- versus post-covid). Thus, in year-2020, $PM_{2.5}$ concentrations are decreasing over time (which is typical for the January to April seasonal pattern in $PM_{2.5}$); concentrations were higher-than-expected pre- and post-covid, but the size of the anomaly is greater post- than pre-covid.

For ozone, mixing ratios (units: ppb) are 36 pre-covid and 43 post-covid, compared to expected levels of 37 pre-covid and 46 post-covid; D values (unitless) are -0.08 pre-covid, -0.37 post-covid. Those values indicate that post-covid year-2020 ozone mixing ratios are 3 ppb (7%) lower than expected (i.e., a post-covid comparison of actual versus expected), and are 7 ppb (19%) higher than pre-covid (i.e., a comparison of actual mixing ratios pre- versus post-covid). Thus, in year-2020, ozone levels are increasing over time (which is typical for the January to April seasonal pattern for ozone); levels were lower-than-expected pre- and post-covid, but the size of the anomaly is greater post- than pre-covid. Thus, the temporal patterns for ozone are nearly opposite those for $PM_{2.5}$.

Conclusions here are robust to the temporal correction method. Selecting an alternative temporal correction method might modestly shift up or down the corrected historical median concentrations (blue line, Fig. 1 right-panels), but that shift would not alter the year-2020 concentrations (red line, Fig. 1 right-panels) and so would be unlikely to suggest, e.g., that post-covid $PM_{2.5}$ concentrations are substantially lower-than-expected based on historical trends plus year-2020 concentrations pre-covid.

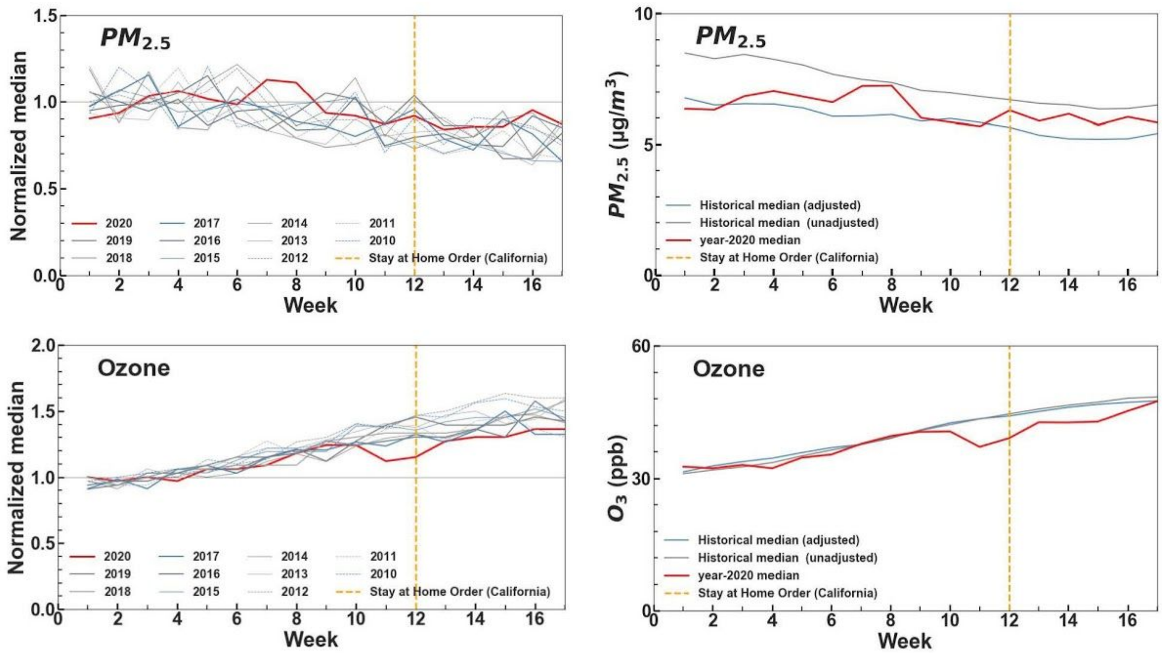

Fig. 1. Year-2020 $PM_{2.5}$ concentrations and ozone mixing ratios (red lines) compared to 2010-2019 concentrations/mixing ratios (grey/blue lines). Left panels show historical (2010-2019) and 2020 weekly median $PM_{2.5}$ concentrations (upper) and ozone mixing ratios (lower), normalized to the January average for that year (i.e., dividing all weekly median concentrations by that year's average of January's weekly medians). Right panels show weekly 10-year median concentrations/mixing ratios with (blue line) and without (grey line) temporal correction, and the year-2020 median (red line), for $PM_{2.5}$ (upper) and ozone (lower).

The robust difference approach provides another metric to quantify the impacts of the covid response on air quality. We aggregated the "robust difference" results by state and for the whole US (Fig. 2). For $PM_{2.5}$, a striking finding is that the robust differences are similar across the entire analysis period. Conditions post- versus pre-covid are not dramatically different. In fact, the median "robust differences" values are a little greater than zero post-covid, meaning that to the extent that there is a deviation, $PM_{2.5}$ concentrations nationally are higher, not lower, than expected. This finding was unexpected given the large reductions in social and economic activity implied by "stay-at-home" orders.

Robust differences (Fig. 2) reveal greater deviations for ozone than $PM_{2.5}$. The noticeable ozone decline starts during week 10, and the strongest deviations are during weeks 11-12. This is slightly before the first official stay-at-home order (California), which was during week 12. (In many locations, social and economic activity was curtailed before the official stay-at-home orders, as people saw events in Italy, China, and other locations strongly affected by the pandemic.) However, the reduction in ozone was short-lived. By week 17, ozone concentrations were nearly back to expected concentrations. Therefore, it is not clear to what extent the ozone change was due to the covid response.

Fig. 2 shows results from six large states, several of which (CA, WA, and NY) implemented strict and abrupt covid policies. For example, concentrations in California for $PM_{2.5}$ and ozone have been lower than expected from one week before the stay-at-home order until week 16 ($p<0.01$), but in week 17 are closer to the expected concentration. Of the six states in Fig. 2 (lower), only two (CA, IL) exhibit lower-than-expected concentrations for several weeks post-covid. The remaining four states (FL, NY, TX, WA) generally have post-covid concentrations that are, for $PM_{2.5}$, higher-than-expected (in three states [FL, NY, TX], the same holds pre-covid) and, for ozone, mixed (i.e., some weeks higher- and some weeks lower-than-expected).

Fig. 2 does not directly account for the fact that stay-at-home orders commenced on different dates for different states. In addition, actual behavior changes could both precede and lag any actual order (25). Fig. 3 presents a similar investigation as in Fig. 2 (upper row), but adjusting the time-axis to align with the date of a state's stay-at-home order (Table S1); in this way, Fig. 3 focuses more directly on the impact of the stay-at-home order.

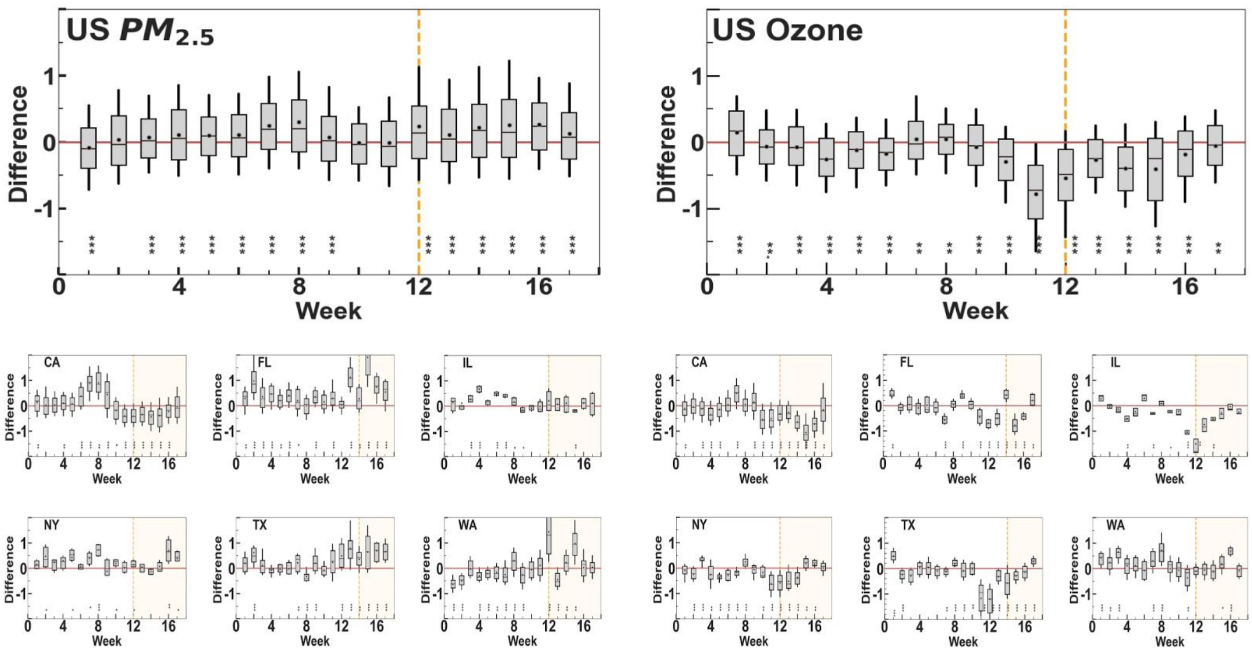

Fig. 2. Robust differences (equation 1) between year-2020 and the long-term average for that week, for $PM_{2.5}$ concentrations (left) and ozone mixing ratio (right) for the US (top row) and for 6 large US states: California, Florida, and Illinois (middle row); New York, Texas, and Washington (bottom row). The start date for stay-at-home orders differs by state, as shown in the figure for that state. (The upper plot indicates timing of the first stay-at-home order in the US: week 12 [California].) Y-axis is the "robust differences" (see text): a value of 0 means the year-2020 concentration is equal to the long-term median, a value of 1 means year-2020 is 1 IQR (interquartile range) above the long-term average. X-axis is time: weeks of the year for 2020 (e.g., week 1 is January 1-7). Asterisks indicate statistical significance via t-test: *** p<0.01, ** p<0.05, * p<0.1.

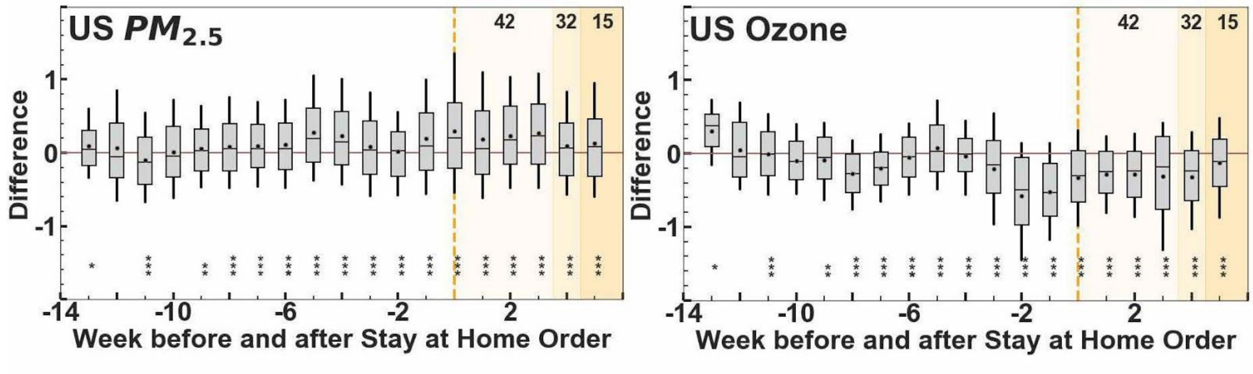

Fig. 3. Robust differences (equation 1) between year-2020 and the long-term average for that week, for $PM_{2.5}$ concentrations (left) and ozone mixing ratios (right) for the US, with time adjusted to match the state's stay-at-home order. These plots are analogous to Fig. 2 (upper row), but with time adjusted state-by-state to be weeks before / after the covid stay-at-home order. The week during which a state's stay-at-home order was enacted is labeled as week 0. Numbers in the upper right (42, 32, 15) indicate the number of states with data in that range: 42 state enacted stay-at-home orders 3 or more weeks prior to week #17 of the year (i.e., the last week for which we have data), 32 states enacted stay-at-home orders 4 or more weeks before week #17, and 15 states enacted stay-at-home orders 5 or more weeks before week #17 (see Table S1).

An interactive Tableau map provides year-2020 D values by state and week:
PM2.5 animation:
https://public.tableau.com/profile/bujin3200#!/vizhome/USPM2_52020RobustDifferenceMap/PM2_5MapUS?publish=yes

Ozone animation:
https://public.tableau.com/profile/bujin3200#!/vizhome/USOzone2020RobustDifferenceMap_15889607934170/OzoneMapUS

[Note: we will work with the journal to link to this interactive site, following the journal's preferences for how to do so.]

Consistent with Fig. 2, in the animation ozone concentrations are lower-than-expected in week 11 in all states (exception: Alaska). We used the median "robust difference" value by week to determine which states had lower-than-expected concentrations ($p<0.1$) for all weeks post-covid. We found that no state is lower-than-expected in all weeks for $PM_{2.5}$, and only one state (California) is consistently lower-than-expected in all weeks for ozone. Arizona comes close for ozone and $PM_{2.5}$, but neither pollutant was lower-than-expected during week 17. The low-ozone anomaly for California decreased in size at the end of April (26).

3.2 Changes in NO_2 Levels

We also analyzed a small dataset for changes in urban NO_2 concentrations, which is primarily emitted by combustion sources such as traffic and power plants. Given the traffic reductions implied by stay-at-home orders, we expect larger changes in NO_2 than in $PM_{2.5}$ and/or ozone concentrations. Unfortunately, EPA had not yet released historical NO_2 data for year-2020. EPA does post real-time (non-QA checked) NO_2 data; some non-EPA sources routinely "scrape" (download) those data. For example, the AQICN website (www.aqicn.org) scrapes and posts air pollution data for many countries globally. We downloaded AQI (Air Quality Index) readings from AQICN for NO_2 for three cities: Los Angeles, CA, New York, NY, and Seattle, WA. All three of these cities had strong public health, political, and social responses to covid. We investigated analogous questions as were addressed above, using monitors in those cities with at least 3 years of data. For the concentration range of interest, the NO_2 AQI is nearly equal to the NO_2 mixing ratio (ppb) (27).

Results for NO_2 for the three cities (Figs. 4 and S3) indicate that post-covid NO_2 AQI values are substantially lower than expected. Defining pre- and post-covid as above (i.e., as means of weekly medians for weeks 1-10 and 11-17, respectively) and averaging across the three cities, we find the average NO_2 AQI (unitless) is 16 pre-covid and 9 post-covid, compared to expected values of 17 pre-covid and 13 post-covid; D values (unitless) are -0.10 pre-covid, -0.57 post-covid. Those values indicate that post-covid year-2020 NO2 AQI values are 4 units (31%) lower than expected (i.e., a post-covid comparison of actual versus expected), and are 7 units (44%) lower than pre-covid (i.e., a comparison of actual AQI pre- versus post-covid). Thus, in year-2020, NO_2 AQI is decreasing over time (which is typical for the January to April seasonal pattern for NO_2); levels were lower-than-expected pre- and post-covid, but the size of the anomaly is greater post- than pre-covid. There is some variability across cities: post-covid NO_2 AQI values are 39% (LA), 38% (NYC), and 20% (Seattle) lower than expected for that city; post-covid D values are -0.64 (LA), -0.63 (NYC), and -0.44 (Seattle). Post-covid concentrations of a traffic-related pollutant (NO_2) are thus much lower than pre-covid and also than expected values.

The changes for NO_2 are much larger than for $PM_{2.5}$ and ozone. Consistent with those results, satellite data also indicate that NO_2 levels in the US are generally lower post- than pre-covid (28); however, a simple pre- versus post-covid NO_2 analysis provides only a weak comparison because NO_2 AQI values typically are lower during weeks 11-17 than during weeks 1-10, even without covid-related responses.

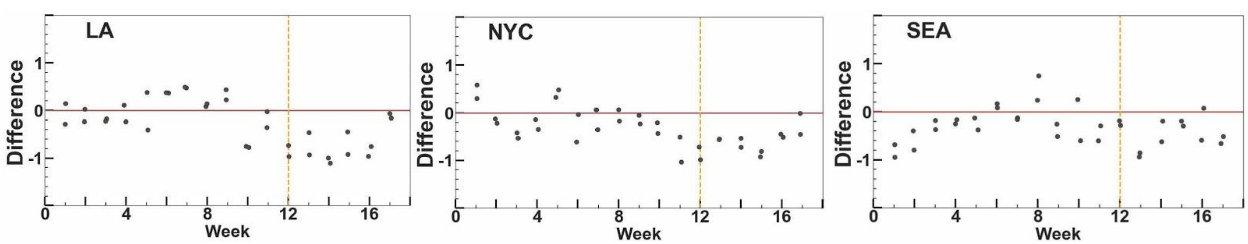

Fig. 4. "Robust difference" for AQI (Air Quality Index) for NO_2 for year-2020 versus medium-term historical data (all years available on a private website; 5 years maximum available), for Seattle (left), New York (center) and Los Angeles (right). Each circle represents the weekly median for one monitor.

Important limitations of the NO_2 data used here include the facts that here they are only obtained for a few cities, they were "scraped" from the EPA website by a third-party (www.aqicn.org) and have not been QA checked by EPA, and they have only 3 years of historical data so we cannot conduct a 10-year temporal correction. As a data-completeness check for NO_2, each year must have 75% of expected days (for year-2020, 75% of pre-covid and also of post-covid expected days) in order to be included; each city has a small number of monitors on AQICN (2 monitors per city) with historical data.

3.3 Potential effects of non-covid factors

We also examined the influence of two non-covid factors on air pollution: meteorology, and upwind ozone entering the US. These factors could potentially enhance or offset the effects of any covid-related changes in emissions. Our analysis suggests that neither of these factors can fully explain the observed concentration patterns.

We used output from ERA5, an ECMWF reanalysis product, over a rectangular box encompassing the contiguous US to investigate meteorological changes (Figs. S4, S5, and S6) (29). We used observations from two remote upwind sites (Mauna Loa, Hawaii [MLO] and Trinidad Head, California [THD] Fig. S8) operated by the US National Oceanic and Atmospheric Administration Global Monitoring Laboratory (NOAA GMD) (30) to investigate large-scale changes affecting upwind ozone.

The meteorological parameters we examined are dew point, planetary boundary-layer (PBL) height, wind speed, temperature, solar insolation, and precipitation. If, for example, PBL height or wind speed were lower-than-average, that aspect could potentially explain higher $PM_{2.5}$ concentrations (i.e., because pollution would be diluted over a smaller volume). But, the post-covid data (Figs. S4 and S5) do not reveal PBL or wind speed values that are unusually or consistently low. Similarly, higher temperatures could potentially increase the formation of ozone or secondary $PM_{2.5}$, but temperatures (Figs. S4 and S5) are not unusually or consistently high. Rather, average post-covid temperatures across the US fall towards the low end of the historical range; this, combined with the drop in average solar insolation in week 11 (precipitation also increased (31); weather in the US was wet and cloudy that week), likely contributes to the relatively low ozone during this time. In terms of transport from upwind locations, two upwind background sites in California (THD) and Hawaii (MLO) (30,32) exhibit lower-than-expected ozone concentrations around the time of the covid response, but not to the same degree as seen above at the EPA sites. Overall, additional analyses will be needed to ascertain how much of 2020 ozone anomalies seen over the US are due to covid-related vs. meteorological and transport effects.

4. Discussion

The EPA data we analyzed indicate that, in the US post-covid, comparing year-2020 to seasonal and long-term trends, there have been only modest and inconsistent changes in concentrations for two of the most important air pollutants: fine particulate matter ($PM_{2.5}$) and ozone. $PM_{2.5}$ concentrations are slightly higher than expected; ozone concentrations are lower. The decrease for ozone is strongest for the ~2 weeks prior to the earliest covid stay-at-home order, and the anomaly has lessened over time since those orders were announced. This paper analyzed air quality data from across the entire US. Therefore it focuses on identifying possible broad and wide scale changes in pollution. It is possible that analyses of data from individual locations, cities, or areas, will reveal different, potentially larger impacts than are reported here.

Results reveal patterns and trends, but do not reveal causation. Additional work would be needed to shed light on the extent to which the observed changes are attributable to covid-related changes (e.g., stay-at-home orders) versus other explanations. While major reductions in vehicle traffic are implied by "stay at home", traffic is but one of many contributors to $PM_{2.5}$. In addition, stay-at-home orders could potentially increase some emissions (e.g., residential wood combustion, backyard BBQ cooking). Emissions might nonlinearly follow activity level (e.g., if traffic-reductions are primarily from newer, lower-emitting cars, while older and higher-emitting vehicles preferentially stay in use) or could be offset (e.g., if workplace electricity consumption declines but household electricity consumption increases or increases at times-of-day when dirtier generators (coal) are more prevalent).

The difference between the NO_2 response (Fig. 5) and $PM_{2.5}$ and ozone responses (Fig. 2) is striking. Urban NO_2 is dominated by traffic emissions. However, ambient $PM_{2.5}$ includes both primary (directly-emitted) and secondary (forms in the atmosphere from chemical reactions) components. Ground-level ozone is secondary: it forms in the atmosphere from reactions involving volatile organic compounds and oxides of nitrogen. Many sources emit $PM_{2.5}$ and/or precursor for $PM_{2.5}$ and ozone, and the resulting activity-emission-concentration relationships are sensitive to a range of atmospheric processes. In contrast, urban NO_2 is dominated by one source (traffic) and so there is a much more direct connection between changes in activity, emissions, and concentrations. We included NO_2 here despite the limitations of the dataset in part because, relative to $PM_{2.5}$ and ozone, NO_2 may be a more direct indicator of changes in one specific activity (traffic). Future releases of additional QA-checked year-2020 monitoring data (NO_2 and otherwise) will enable additional analyses of NO_2 and other changes in a larger dataset.

Comparatively larger changes in air pollution have been reported in other countries. In Barcelona, Spain, concentrations of NO_2 and black carbon were 50% lower during stay-at-home orders, but the weather was relatively windy and rainy (12). Ozone concentrations in Barcelona increased by 50%, perhaps related to a shift in chemical regime: NO_2 reductions can reduce the amount of titration (destruction) of ozone by NO_x. In Delhi, India, measured concentrations of PM_{10}, $PM_{2.5}$, NO_2, and CO were reported to be substantially lower (for PM_{10} and $PM_{2.5}$, ~2× lower) during shelter-in-place (17). In general, these methods did not fully account for random and systematic temporal variability, for multiple time-scales, as was done here.

There may be many reasons why we do not observe consistent and large reductions in $PM_{2.5}$ and ozone concentrations across the US, despite the enormous social and economic changes brought about by covid and stay-at-home orders. First, there is substantial variability -- random and systematic -- which complicates finding a “signal” in post-covid changes in air pollution. However, we expect these effects would not completely hide large concentration changes, especially given the size of our dataset. Second, ozone and much of $PM_{2.5}$ are secondary (they form in the atmosphere from chemical reactions of precursor emissions). Those emissions come from many different sources. As a result, the connection between changes in source activity, emissions, and concentrations is complex. Reducing one or a small number of emission categories may or may not lead to large change in ozone or $PM_{2.5}$. Since NO_2 is, to a greater extent, a primary pollutant, we expect (and see) larger changes. Third, EPA has not yet released year-2020 data for several criteria pollutants, including NO_2; investigation of additional pollutants will provide a more complete picture regarding changes in air pollution from responses to covid. Finally, because of decades of effective regulatory policies, air pollution levels in the US are (while causing substantial adverse health effects in the US) much lower than many other countries in the world (33-35). Findings here suggest that covid-related emission reductions did not in general lower average US $PM_{2.5}$ beyond their typical range of variability, and did not consistently lead to lower-than-expected ozone concentrations across the country.

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Supplemental information

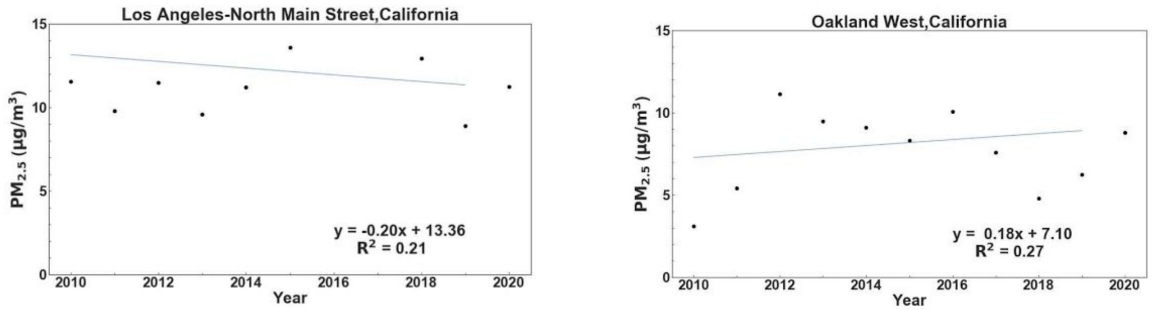

Fig. S1. Example of the temporal corrections for $PM_{2.5}$: Los Angeles North Main Street monitor (left) and Oakland West monitor (right), both in California, for week 14. Slopes (units: μg m^{-3} y^{-1}) are 0.18 (right) and -0.20 (left). These two monitors were chosen as examples because they have similar slopes but with opposite signs; and, the slope for the left plot is approximately equal to the national median slope.

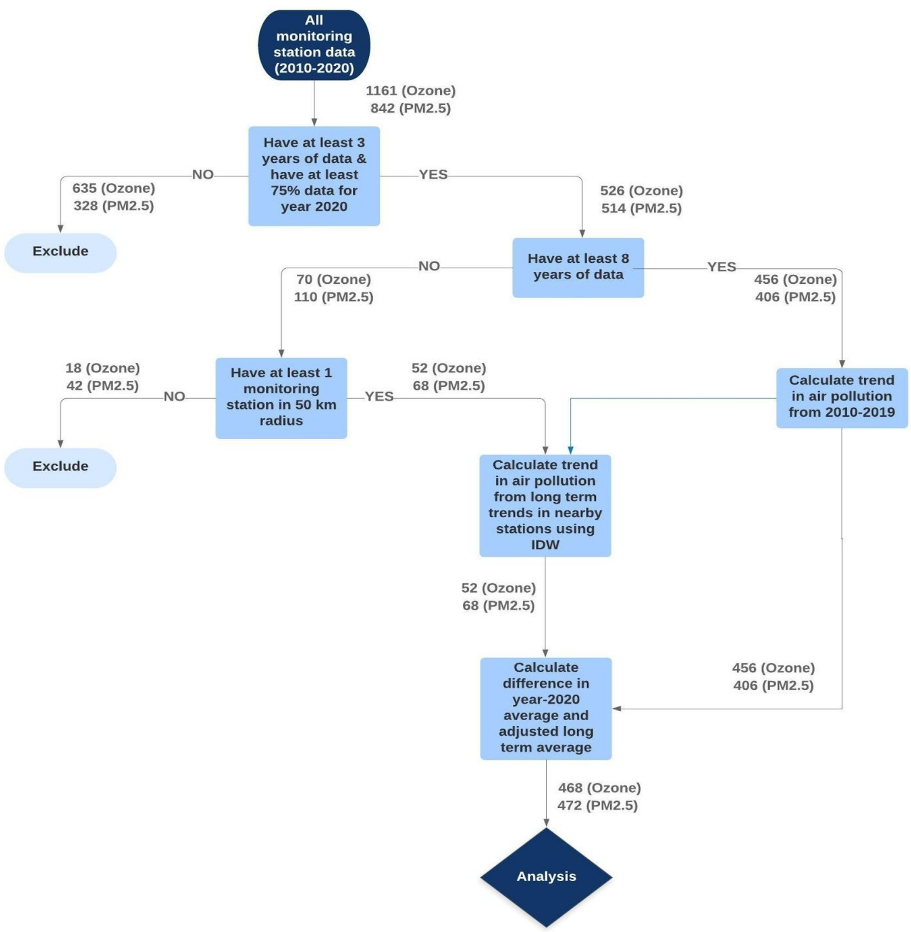

Fig. S2. Monitor inclusion rule flow diagram. Numbers indicate the number of monitors.

Fig. S3. Weekly-median AQI (Air Quality Index) for NO_2, for year-2020 and medium-term historical data (all years available on a private website; 5 years maximum available), for Seattle (left), New York (center) and Los Angeles (right).

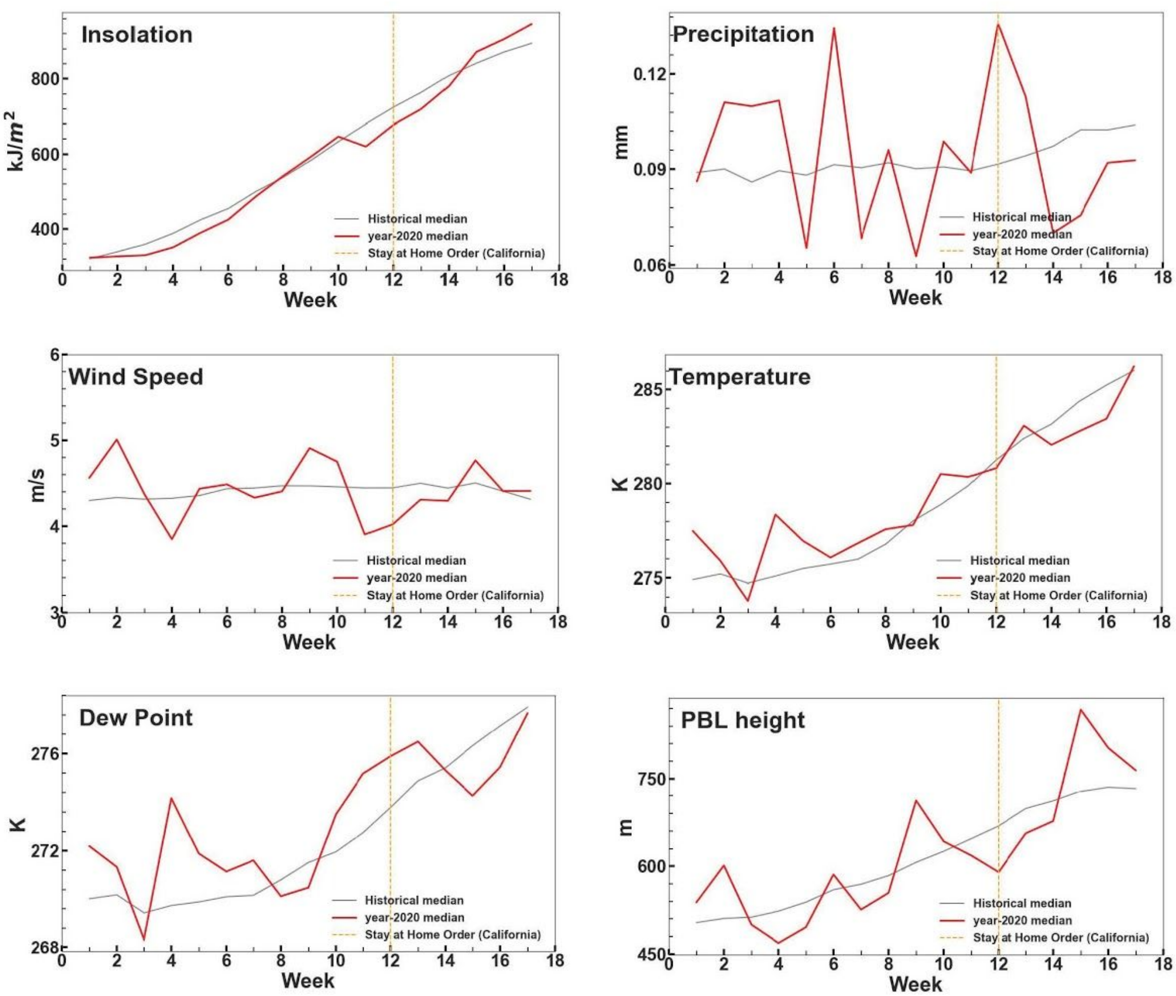

Fig. S4 Meteorological variables during 2020 (red line) versus 2010-2019 (grey line). Values are weekly medians of area-weighted daily-mean values, taking the mean value across years.

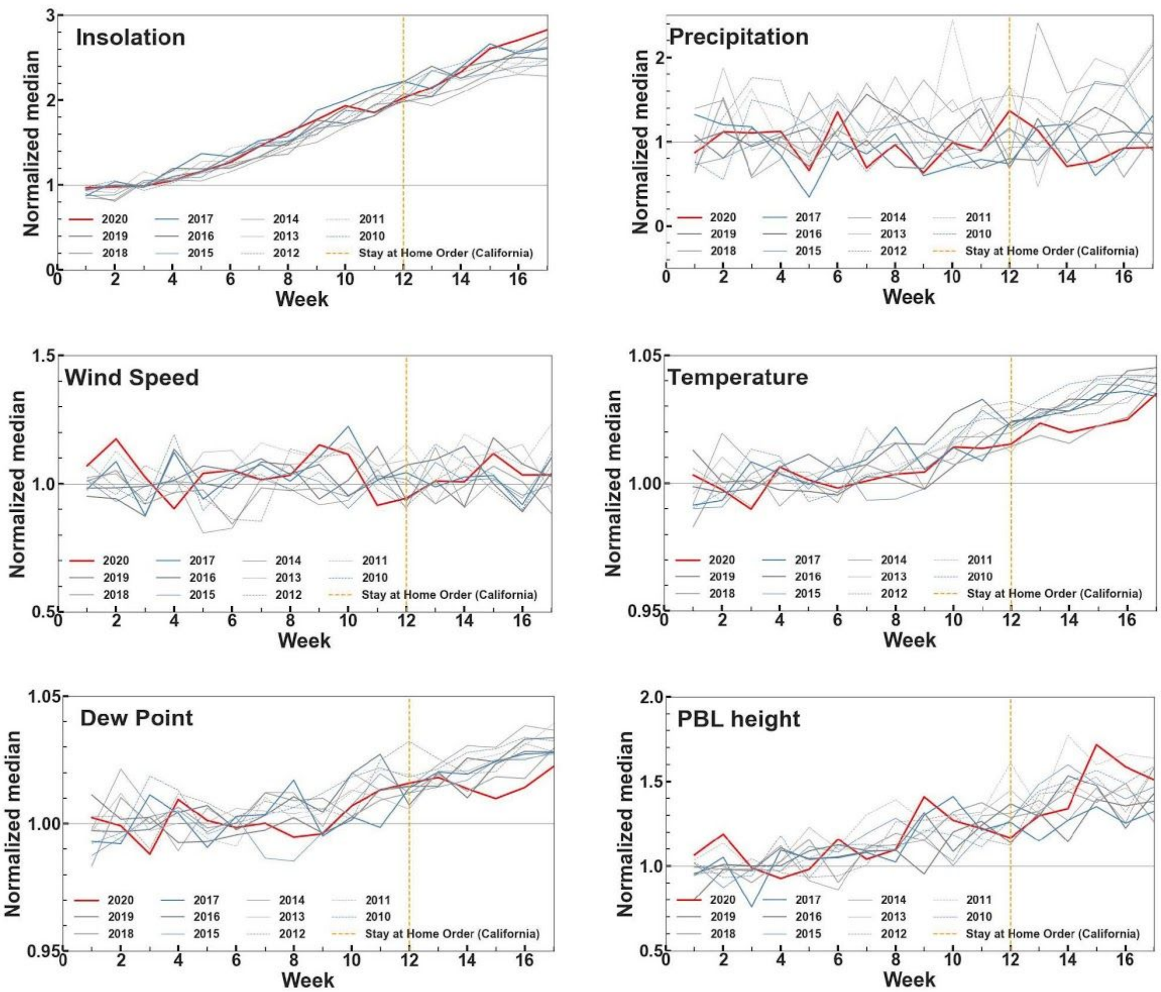

Fig. S5 Meteorological variables during 2020 (red line) versus 2010-2019 (grey/blue lines). Values are weekly medians of area-weighted daily-mean values.

Fig. S6. Map of contiguous US ("CONUS") for which meteorological variables were calculated.

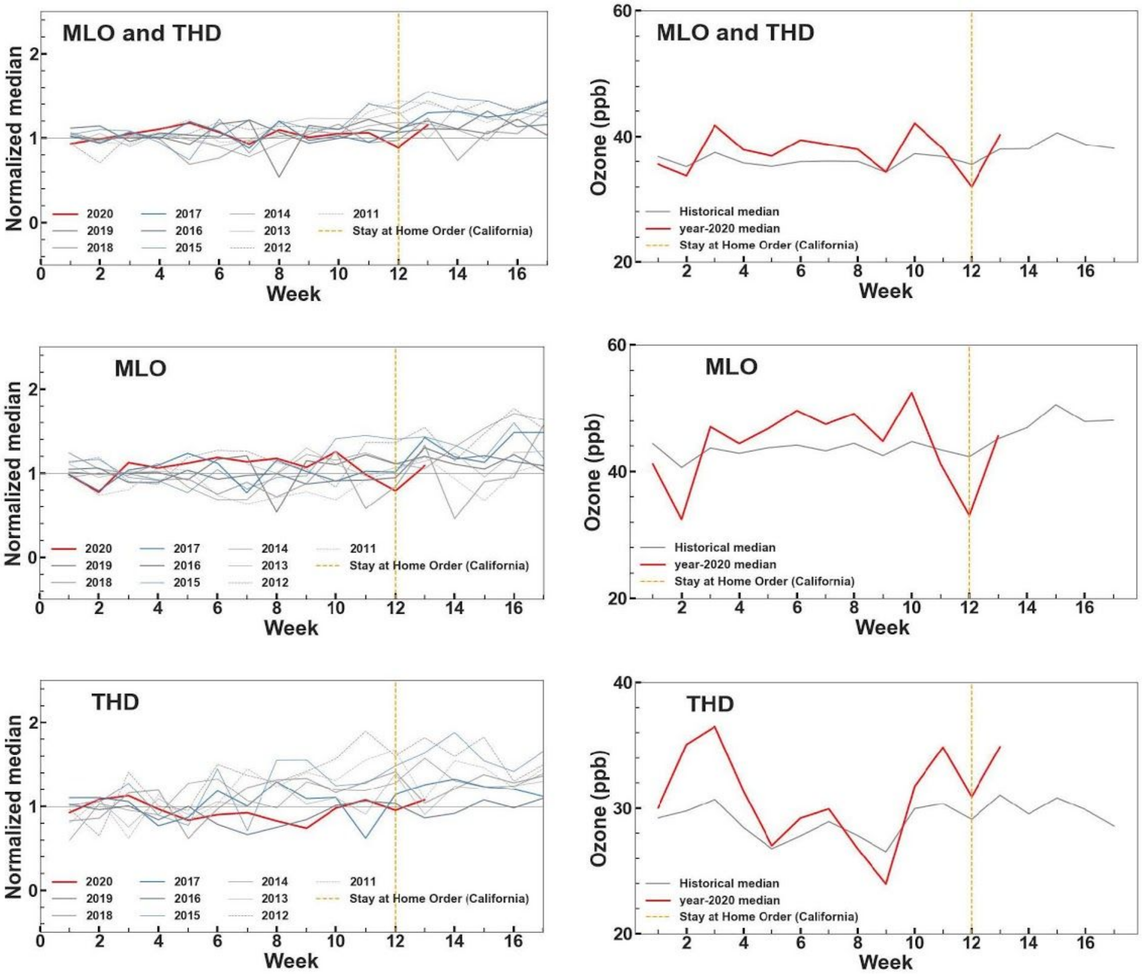

Fig. S7 Ozone concentrations at two upwind locations (Mauna Loa Observatory, Hawaii [MLO] and Trinidad Head, California [THD]) for 2010-2020, analyzed in the same manner as data in Fig. 1.

Table S1. Stay-at-home date of each state

State	Stay at Home Order	State	Stay at Home Order
Alabama	2020-04-04	Montana	2020-03-28
Alaska	2020-03-28	Nebraska	
Arizona	2020-03-31	Nevada	2020-04-01
Arkansas		New Hampshire	2020-03-27
California	2020-03-19	New Jersey	2020-03-21
Colorado	2020-03-26	New Mexico	2020-03-24
Connecticut	2020-03-23	New York	2020-03-22
Delaware	2020-03-24	North Carolina	2020-03-30
District of Columbia	2020-04-01	North Dakota	
Florida	2020-04-03	Ohio	2020-03-23
Georgia	2020-04-03	Oklahoma	
Hawaii	2020-03-25	Oregon	2020-03-23
Idaho	2020-03-25	Pennsylvania	2020-04-01
Illinois	2020-03-21	Puerto Rico	2020-03-15
Indiana	2020-03-24	Rhode Island	2020-03-28
Iowa		South Carolina	2020-04-07
Kansas	2020-03-30	South Dakota	
Kentucky	2020-03-26	Tennessee	2020-03-31
Louisiana	2020-03-23	Texas	2020-04-02
Maine	2020-04-02	Utah	
Maryland	2020-03-30	Vermont	2020-03-25
Massachusetts	2020-03-24	Virginia	2020-03-30
Michigan	2020-03-24	Washington	2020-03-23
Minnesota	2020-03-27	West Virginia	2020-03-24
Mississippi	2020-04-03	Wisconsin	2020-03-25
Missouri	2020-04-06	Wyoming	

Source: "See Which States and Cities Have Told Residents to Stay at Home" https://www.nytimes.com/interactive/2020/us/coronavirus-stay-at-home-order.html (accessed April 20, 2020). See also, "See Which States Are Reopening and Which Are Still Shut Down" https://www.nytimes.com/interactive/2020/us/states-reopen-map-coronavirus.html

Table S2a. Year-2020 concentrations and robust differences by state

$PM_{2.5}$
https://public.tableau.com/profile/bujin3200#!/vizhome/Ozoneconcentrationandrobustdifferencepreandpostcovid/PM2_5USRobustDifferenceTable?publish=yes

Ozone
https://public.tableau.com/profile/bujin3200#!/vizhome/Ozoneconcentrationandrobustdifferencepreandpostcovid/OzoneUSRobustDifferenceTable?publish=yes

[Note: we will work with the journal to link to these data, following the journal's preference for how to do so.]

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