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Changes in criteria air pollution levels in the US before, during, and after Covid-19 stay-at-home orders: Evidence from regulatory monitors



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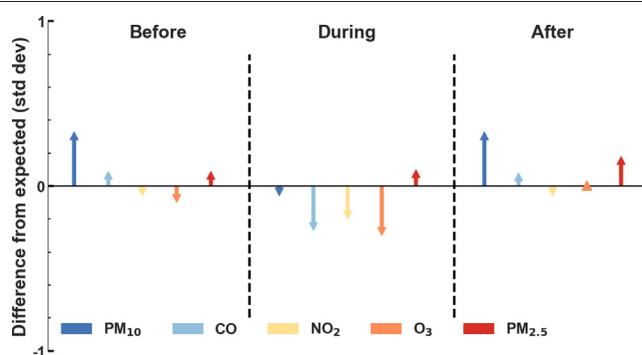
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HIGHLIGHTS

- Impacts of stay-at-home orders on air pollution were evaluated using EPA monitoring data from 100s of stations across the US.
- During stay-at-home orders, ozone, NO₂, CO and PM₁₀ were lower and PM_{2.5} were higher than expected levels by 1%–30% of their IQR.
- Concentration anomalies ended only 5–6 weeks after stay-at-home orders were issued.
- Ozone, NO₂, and CO concentrations returned to expected levels and PM_{2.5} and PM₁₀ levels were higher than expected.
- Reductions in ozone, NO₂, and CO levels were modest and short-lived. PM₁₀ levels did not change and PM_{2.5} levels increased.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:

Received 30 October 2020

Received in revised form 16 December 2020

Accepted 18 December 2020

Available online 2 January 2021

Editor: Jay Gan

Keywords:

Air pollution and Covid-19

Air pollution and stay-at-home orders

ABSTRACT

The widespread and rapid social and economic changes from Covid-19 response might be expected to dramatically improve air quality. However, national monitoring data from the US Environmental Protection Agency for criteria pollutants (PM_{2.5}, ozone, NO₂, CO, PM₁₀) provide inconsistent support for that expectation. Specifically, during stay-at-home orders, average PM_{2.5} levels were slightly higher (~10% of its multi-year interquartile range [IQR]) than expected; average ozone, NO₂, CO, and PM₁₀ levels were slightly lower (~30%, ~20%, ~27%, and ~1% of their IQR, respectively) than expected. The timing of peak anomaly, relative to the stay-at-home orders, varied by pollutant (ozone: 2 weeks before; NO₂, CO: 3 weeks after; PM₁₀: 2 weeks after); but, by 5–6 weeks after stay-at-home orders, the concentration anomalies appear to have ended. For PM_{2.5}, ozone, CO, and PM₁₀, no US state had lower-than-expected pollution levels for all weeks during stay-at-home-orders; for NO₂, only Arizona had lower-than-expected levels for all weeks during stay-at-home orders. Our findings

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Criteria air pollution
Stay-at-home orders
COVID-19

show that the enormous changes from the Covid-19 response have not lowered PM_{2.5} levels across the US beyond their normal range of variability; for ozone, NO₂, CO, and PM₁₀ concentrations were lowered but the reduction was modest and transient.

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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 during Covid could reveal, for example, how 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. Analogous investigations have 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 (Pope III et al., 1992); copper smelters throughout the US (Pope III et al., 2007)), widespread power outage in the Northeastern US (Hu et al., 2006), new regulation such as a coal ban in Dublin (Clancy et al., 2002) and a congestion charging scheme in London (Kelly et al., 2011), and the 1996 Atlanta (Friedman et al., 2001; Peel et al., 2010) and 2008 Beijing (Rich et al., 2012; Li and Chen, 2010) Olympics. However, societal changes attributable to the Covid response are unprecedented in size, scope, and speed.

Air pollution concentrations at a given location vary on time scales from seconds to years; some variability is random or quasi-random, other variability is systematic (i.e., non-random). Temporal variability is caused by changes in emissions and meteorology and their associated impacts on rates of transport, production, removal, and dilution. The net result is that because of random and systematic temporal variability, concentrations during Covid may be different than before Covid (e.g., one month or one year earlier) for reasons unrelated to the societal response 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 (Pope III et al., 1992; Pope III et al., 2007; Hu et al., 2006; Clancy et al., 2002; Kelly et al., 2011; Friedman et al., 2001; Peel et al., 2010; Rich et al., 2012; Li and Chen, 2010; Henschel et al., 2012; Henneman et al., 2016).

Our paper also adds to the existing literature exploring Covid-related impacts on air pollution and related activity levels (Tobias et al., 2020; He et al., 2020; Venter et al., 2020; Kambalagere, 2020; Anjum, 2020; Mahato and Ghosh, 2020; Shrestha et al., 2020; Bauwens et al., 2020; Xu et al., 2020; Dutheil et al., 2020; Chauhan and Singh, 2020; Alfarra et al., 2020; Tanzer-Gruener et al., 2020; Berman and Ebisu, 2020; Goldberg et al., 2020; Xiang et al., 2020; Dantas et al., 2020; Bao and Zhang, 2020; Kerimray et al., 2020; Sharma et al., 2020; Chen et al., 2020; Li et al., 2020; Kugel and Feeser, 2020). Much of the news in the popular press regarding impacts of Covid on air pollution emphasizes that concentrations have improved during Covid (CNN, 2020; Lewis, 2020; Hoeller, 2020; Freedman and Tierney, 2020; Monks, 2020; Mervosh et al., 2020); our investigation aims to test those claims using a national dataset of in-situ concentration measurements. We present two approaches for deriving “expected” concentrations (i.e., in the absence of Covid responses) against which to compare observed concentrations: (1) our main approach is temporally corrected. (2) We also employ a secondary approach (“sensitivity analysis”) that is temporally and weather corrected using regression techniques. We do not attempt to shed light on the specific causes of any changes nor on regulatory implications.

This paper uses nationwide, publicly-available monitoring data from the US Environmental Protection Agency (EPA) to investigate changes in criteria air pollutants, before, during, and after Covid stay-at-home orders. These data represent the largest source of publicly-available and robust measurements of criteria air pollutants for the US. Our methods control for random and systematic variability on multiple time scales, and by state and nationally. There have been many investigations into how air pollution levels have changed during Covid; yet, to our knowledge, no prior research has systematically analyzed changes in in-situ measured criteria air pollution concentrations before, during, and after stay-at-home orders across the US.

2. Methods

2.1. General approach

We use “before”, “during”, and “after stay-at-home orders” as general terms: “before stay-at-home orders” refers to weeks before stay-at-home orders, when, in 2020, Covid had little or no impact on activities in the US; “during stay-at-home orders” refers to a few weeks preceding the stay-at-home order dates and weeks during stay-at-home orders; “after stay-at-home orders” refers to weeks after the states have removed stay-at-home orders. Those labels are applied to specific weeks, as described in the analyses below. The scope of the stay-at-home orders varies from state to state. The term “stay at home” refers to a specific requirement (also called “shelter in place”), with a specific start and end date (Table S1), announced by most state governments.

2.2. Data acquisition and selection

We employ publicly-available daily-average in-situ air pollution concentrations measured at EPA monitors. We downloaded data from the EPA AirData website (<https://www.epa.gov/outdoor-air-quality-data/download-daily-data>) on September 2, 2020. As of September 2, 2020, data for two pollutants are available from the EPA for the time-period of interest for Covid (March 2020 and later): fine particulate matter (PM_{2.5}, i.e., particles with aerodynamic diameter less than or equal to 2.5 μm) and ozone. Other pollutants or averaging times are currently unavailable from EPA.

We also downloaded and analyzed NO₂, CO, and PM₁₀ data from the Environmental Sensor Data Repository (ESDR; <https://esdr.cmucreatelab.org>). ESDR data are EPA measurements that EPA has provided in real-time but not yet in an archival or database format; ESDR saves (“scrapes”) those real-time data and shares them in their raw form. (Available EPA data for SO₂ were too imprecise to support a robust analysis.)

We started by downloading all data (daily 24-hour average concentrations for PM_{2.5} and PM₁₀, daily 8-h maximum for ozone and CO, daily 1-h maximum for NO₂; December 18, 2009 - December 31, 2019) for all monitors from EPA AirData. We then downloaded the year-2020 (January 1, 2020 - September 1, 2020) PM_{2.5} and ozone data from EPA AirData and NO₂, CO, SO₂, and PM₁₀ data from the ESDR website for all monitors with one or more days of data in year-2020. (As mentioned above, SO₂ data were downloaded but were too imprecise to support robust analysis.) Finally, we matched the historical and year-2020 data based on the monitor's latitude and longitude. We restricted the analysis to consider a specific window of days each year: for 2020, the window is January 1–September 1 (245 days); for years 2010–2019, the window is December 18–September 15 (Total: 273 days), i.e., the

year-2020 range ± 2 additional weeks. Data outside of those windows were excluded from the analysis.

Analyses extend through September 1, 2020 (the 245th day of 2020 and the completion of the 35th week of the year). Weeks are sequential: week 1 is days 1–7 of the year, week 2 is days 8–14 of the year, etc. (Table S2). By stopping our analyses at week 35, we avoid the massive wildfires that occurred on the West Coast starting in week 36 (September 4 to September 10) (Cal Fire, 2020; Fuller and Healy, 2020).

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

First, we tested each monitor-year for data sufficiency. For years 2010–2019, if any monitor-year contains <75% of the expected number of days in the target window ($75\% \times 273 = 206$ 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; 78 days) and after the start of Covid (March 19–September 1; 167 days); if either period's data contains <75% of the expected days ($75\% \times 78 \text{ days} = 59 \text{ days}$; $75\% \times 167 \text{ days} = 125 \text{ days}$), then that monitor is excluded.

Second, we ensure that a monitor has a sufficient number of years of valid data to calculate the temporal correction. This step employs the following three data requirements (Fig. S1): (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. (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 under 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 3 closest monitors within 50 km. This approach (3 nearest monitors within 50 km) has been adopted by prior articles (e.g., Brauer et al., 2008). Bravo et al. (2012) state, "a distance of 50 km was chosen because it represented a reasonable distance for extrapolation of observed air pollutant concentrations and has been used previously in epidemiological settings (Hanigan et al., 2006; Lipsett et al., 2011; O'Donnell et al., 2011; Spencer-Hwang et al., 2011), but other distances could have been selected with similar justification." Marshall et al. (2008) reported that this approach (3 nearest monitors within 50 km) yielded better results than two analogous approaches (all monitors within 50 km; and all monitors within 10 km). If there are no other monitors within 50 km, then we exclude that monitor from the analysis.

The AirData and ESDR websites provided year-2020 concentrations for 1141 PM_{2.5}, 1206 ozone, 436 NO₂, 270 CO, and 673 PM₁₀ monitors. Our data completeness algorithm excluded a total of 583 (51%) PM_{2.5}, 543 (45%) ozone, 343 (79%) NO₂, 207 (77%) CO, and 565 (84%) PM₁₀ monitors. Therefore, the results and discussion are based on data from 558 PM_{2.5}, 663 ozone, 93 NO₂, 63 CO, and 108 PM₁₀ monitors. Considering varying sampling frequency for ozone (e.g., sampled only during warm months in some locations), we conducted a sensitivity analysis with additional ozone monitors (total of 949) that have more than 14% data completeness (Fig. S6). Each monitor is in a different location. State-specific results refer to states with monitors that met the inclusion criteria (Table S3).

We downloaded meteorology data (hourly temperature, precipitation, mixing height, and dew point data for US; December 18, 2009 – September 1, 2020) from European Center for Medium-Range Weather Forecasts (ECMWF) ERA5 Reanalysis (Hersbach et al., 2018). Then we extracted hourly meteorological data for each monitoring station and calculated the daily average values. We also analyzed US public transit mobility data from Google Community Mobility Reports (<https://www.google.com/covid19/mobility/>).

As a side-analysis, we examined the influence of upwind ozone entering the US. In principle, upwind pollution levels could potentially enhance or offset the effects of changes in emissions in the US. We used observations from two remote upwind sites (Lassen Volcanic National

Park, California [LAV] and Trinidad Head, California [THD]) operated by, respectively, the US National Park Service and the US National Oceanic and Atmospheric Administration Global Monitoring Laboratory (NOAA GMD) (Finlayson-Pitts and Pitts Jr, 1993).

2.3. Main approach: temporal correction, using robust differences ("D")

We calculate a "robust differences" metric ("D"): the weekly median concentration for 2020, relative to the temporally-corrected historical median, normalized to the interquartile range (IQR).

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

Eq. (1) is calculated for each week ("i") and for each monitor. D_i is the "robust differences" 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 D_i for week 10, we use C_{2020} for week 10, for $C_{h,i}$ and $I_{h,i}$ we use historical data (i.e., years prior to 2020) for weeks 8–12. The "plus/minus 2 weeks" approach for historical data increases the sample size for the comparisons (historic vs year-2020), gives a broader historical comparison than just one week, and helps smooth atypical weeks in the historical dataset.

D is called a "robust" metric because it employs median and IQR rather than mean and standard deviation, so it is not impacted by outliers. $D=0$ would indicate that the year-2020 median is equal to the "expected" value (i.e., the temporally-corrected long-term average median). $D=1$ would indicate that the year-2020 value is one IQR above the expected value; $D=-2$ would indicate two IQRs below the expected value. D reveals whether year-2020 concentrations are higher- or lower-than expected, for before, during, and after stay-at-home order weeks, but does not elucidate their cause nor inform regulatory aspects such as comparisons against national standards.

Temporal correction is needed because air pollutant concentrations exhibit systematic long-term (multi-year) trends that can vary by location (see example temporal collection in Fig. S2). The temporal correction for a monitor in week i is the 10-year slope (i.e., 2010–2019) of weekly-median historical concentrations at that monitor (Fig. 1). In this manner, we compare actual year-2020 measurements to the "expected" level for week i in year-2020, accounting for 10-year trends for that week-of-year at that location. (As a sensitivity analysis, we used 5- rather than 10-year trends; results were similar (Fig. S3).) 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.

2.4. Sensitivity analyses: temporal and weather correction, using regression analyses

As sensitivity analyses, we instead use linear (Eq. (2)) and spline (Eq. (3)) first-order multivariate autoregression to correct for temporal patterns and weather:

$$C_t = \beta_0 + \beta_1(\mathbf{m}_t) + \beta_2(\delta_{y,2020}) + \beta_3(C_{t-1}) + \beta_4(y_t) + \varepsilon_t \quad (2)$$

$$C_t = \beta_0 + bs(\mathbf{m}_t, y, \nu) + \beta_1(\delta_{y,2020}) + \beta_2(C_{t-1}) + \varepsilon_t \quad (3)$$

Here, C_t is the concentration of the pollutant on day t , \mathbf{m}_t is the daily average meteorology (temperature, precipitation, mixing height, and dew point) on day t , " $\delta_{y,2020}$ " is a dummy variable to reveal if the day is in 2020, (C_{t-1}) is the concentration on the previous day (i.e., a 1-day lag), y_t is the year of the date the concentration was recorded, ε_t is

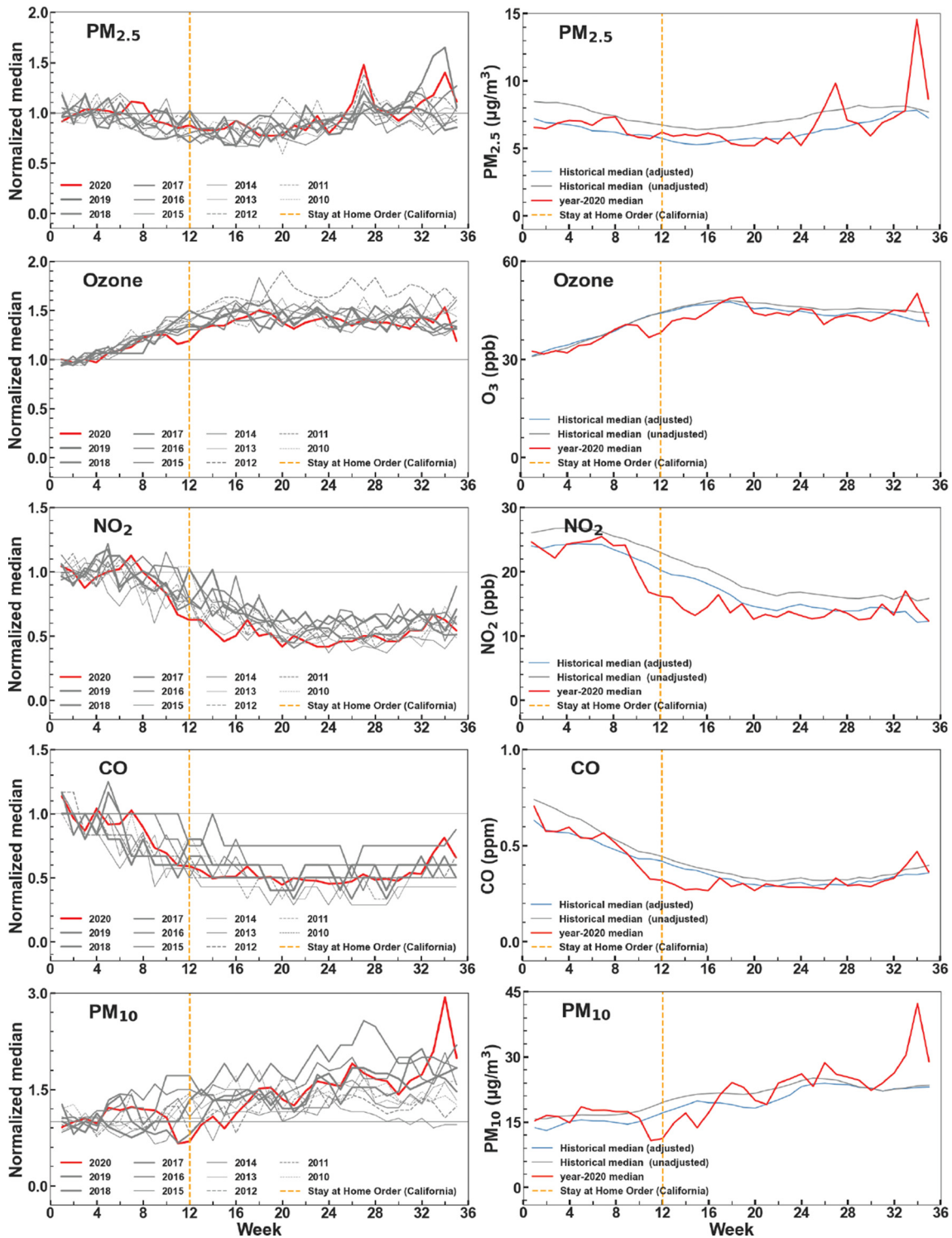


Fig. 1. Year-2020 pollution levels (red lines) compared to 2010–2019 levels (grey/blue lines). Left panels show historical (2010–2019, unadjusted) and 2020 weekly median concentrations normalized to the January average for that year (i.e., dividing all weekly median concentrations by that year’s January’s mean). Right panels show weekly 10-year median pollution levels with (blue line) and without (grey line) temporal correction, and the year-2020 median (red line). The orange vertical dashed line indicates timing of the first stay-at-home order in the contiguous US: week 12 [CA]. These data indicate that except for $PM_{2.5}$, pollution levels exhibited a modest, temporary drop around the time of the first stay-at-home order.

the error, and bs is a b-spline function with degrees of freedom, ν (splines library in R).

As above, data (concentrations, meteorology) are daily-averages, Eqs. (2) and (3) are evaluated for each monitor and week (e.g., there are 44 weeks and 525 $PM_{2.5}$ monitors, so Eqs. (2) and (3) are evaluated 23,100 times for $PM_{2.5}$), and historical data (2010–2019) are “ ± 2

weeks” (e.g., week 10 in year-2020 is matched to historical data from weeks 8–12). When analyzing results from Eqs. (2) and (3), then aggregating across monitors, we define the time axis as the week number before, during, and after the stay-at-home order.

This analysis reveals whether year-2020 concentrations are different from the expected concentrations after correcting temporally and for

meteorology. Eqs. (2) and (3) are autoregressive, explicitly accounting for temporal autocorrelation in the measurements (Fig. S4).

3. Results

3.1. Temporal correction, using robust differences

As described next, concentrations during stay-at-home orders are slightly higher-than-expected for $PM_{2.5}$, and modestly lower-than-expected for ozone, NO_2 , CO, and PM_{10} . The ozone anomaly was largest two weeks before the stay-at-home order; ozone levels returned to expected levels a few weeks after the stay-at-home orders were imposed. The anomalies for NO_2 , CO, and PM_{10} are highest 2–3 weeks after the stay-at-home orders, and then levels returned to expected levels.

Fig. 1 presents year-2020 and 2010–2019 pollution levels. After stay-at-home orders were imposed, $PM_{2.5}$ levels are towards the high end of the historical range, indicating, on average, a modest (~3%) increase relative to expected concentrations. In contrast, average ozone, NO_2 , CO, and PM_{10} levels are lower than expected, with the largest drop occurring during weeks 10–11 (i.e., March 4–18, 2020).

Historical $PM_{2.5}$, NO_2 , CO, and PM_{10} concentrations are lower with temporal correction than without it (Fig. 1, right) because pollution levels generally decrease each year. Ignoring that decrease (by comparing against uncorrected levels) would mean, on average, inappropriately concluding that most weeks are “lower than average”, for any year. In contrast, temporally corrected results accounting for that long term trend (Fig. 1) suggest that $PM_{2.5}$ concentrations during stay-at-home orders are similar to or higher than expected concentrations.

For ozone, the temporal correction is minor (~0.2% per year): ozone levels exhibit year-to-year variability but without a strong 10-year trend. Seasonally, ozone levels generally increase during January to April, reflecting increasing photochemical activity. Therefore, a direct comparison of weeks before vs during stay-at-home orders would incorrectly suggest that ozone levels are higher than expected; that conclusion fails to account for ozone’s seasonal trend. Similarly, NO_2 and CO levels generally decrease during January to April. Hence, direct comparison of pollution levels before vs during stay-at-home would exaggerate the effect of stay-at-home orders on NO_2 and CO levels.

General 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. 2 right-panels), but that shift would not alter the year-2020 concentrations (red line, Fig. 2 right-panels) and so would be unlikely to suggest, for instance, that after stay-at-home orders, $PM_{2.5}$ concentrations are substantially lower-than-expected based on historical trends plus year-2020 concentrations before stay-at-home orders.

Fig. 2 shows week-by-week robust differences before, during, and after the stay-at-home orders (adjusting the time-axis to align with the date of a state’s stay-at-home order); in this way, Fig. 3 focuses directly on the impact of the stay-at-home order: before versus during the order (Fig. 2, left) and during versus after the order (Fig. 2, right). The number of states included in Fig. 3 varies by week because states started and stopped stay-at-home orders on different dates. The air pollution levels in states that have not initiated stay-at-home orders on a given date can be influenced by traffic and economic activity changes in the neighbouring states that imposed a stay-at-home order or vice versa. Therefore we also included week-to-week robust difference results where the time-axis is calendar weeks of the year in 2020 (Fig. S5).

Noticeable ozone, NO_2 , CO, and PM_{10} declines start three weeks before stay-at-home orders, and the strongest ozone deviations occur two weeks before the stay-at-home order. The transit mobility analysis results (Fig. S15) indicate that transit mobility started to decrease from the baseline ~3 weeks before stay-at-home orders, which is consistent

with this timing. (In many locations, people curtailed social and economic activity starting before the official stay-at-home orders (Badger and Parlapiano, 2020; Kroll et al., 2020). However, the pre-stay-at-home order reduction in ozone was not sustained; over time, “D” increases and the size of the anomaly decreases. By six weeks after the stay-at-home orders, ozone concentrations were not significantly different from their expected levels.

We can summarize the differences in Fig. 2 by considering “before” to be the average during weeks 4–14 before the stay-at-home orders, “during” to be the average of weeks 1–3 before and weeks 1–12 during the stay-at-home orders, and “after” to be the average during weeks 1–20 after the stay-at-home orders ended. Core results (Table 1) reveal that during stay-at-home, pollution levels were modestly lower than expected for ozone, NO_2 , CO, and PM_{10} , but not for $PM_{2.5}$. Specifically, during stay-at-home orders, $PM_{2.5}$ levels were higher-than-expected by 10% of its IQR; ozone, NO_2 , CO, and PM_{10} levels were lower-than-expected by 1%–30% of their respective IQRs. Pollution levels were also not precisely at expected levels before the stay-at-home orders; for PM_{10} , before stay-at-home levels were higher than expected by 32% of the IQR; remaining pollutants were between 10% of their IQR lower and 9% of their IQR higher than expected. After the states have reopened, the ozone and NO_2 are close to expected levels (0% - 1% of their IQR lower than expected), $PM_{2.5}$, CO, and PM_{10} are higher than expected (8% - 33% of their IQR).

Fig. 3 shows results before, during, and after stay-at-home orders by state. (Alternative versions of this figure – based on calendar date rather than relative to stay-at-home orders (Fig. S7), or also including states that did not issue a stay-at-home order (Fig. S8) – reveal similar results.) The overall patterns described above (during stay-at-home orders, ozone, NO_2 , PM_{10} , and CO levels (but not $PM_{2.5}$ levels) were modestly lower than expected) are observed for Fig. 3; however, none of the patterns are ubiquitous. Considering each map in Fig. 3 separately, some trends hold for most states but none hold for all states.

3.2. Sensitivity analysis: temporal and weather correction, using regression

As Eq. (2) corrects for temporal trends and meteorology, the estimated coefficients directly indicate whether year-2020 concentrations were higher (positive coefficients) or lower (negative coefficients) than expected. The results from the linear regression analysis mostly agree with the robust difference results (Tables 1 and S5). Specifically, considering all 5 pollutants both before, during, and after stay-at-home orders (15 total comparisons), the sign of the result is the same between the two methods, with two exceptions. (The two exceptions are for before stay-at-home levels of $PM_{2.5}$ and CO; see Table S5. Specifically, the average robust difference for before stay-at-home $PM_{2.5}$ and CO are 0.09, suggesting that $PM_{2.5}$ and CO were slightly higher than expected before stay-at-home orders. In contrast, the regression analysis indicates that before-stay-at-home $PM_{2.5}$ was, on average, $0.28 \mu\text{g}/\text{m}^3$ lower than expected and CO was at the expected level.) Furthermore, the trend in estimated coefficients aggregated by week is similar to the trend in robust differences by week before, during, and after stay-at-home orders. The concentration anomaly for all pollutants except $PM_{2.5}$ started 3–4 weeks before stay-at-home orders and the anomaly decreased over time (Figs. 2 and S10).

The results from spline regression (Eq. (3)) are generally consistent. In some cases the results vary with the degrees of freedom of the spline function. (Specifically, the results for during stay-at-home order PM_{10} and after stay-at-home ozone, NO_2 , and CO varied among spline degrees of freedom; see Table S6a-d.)

3.3. Potential effects of upwind ozone entering the US

Two upwind background sites in California (LAV and THD) (Parrish et al., 2017; Quan et al., 2019) exhibit lower-than-expected ozone

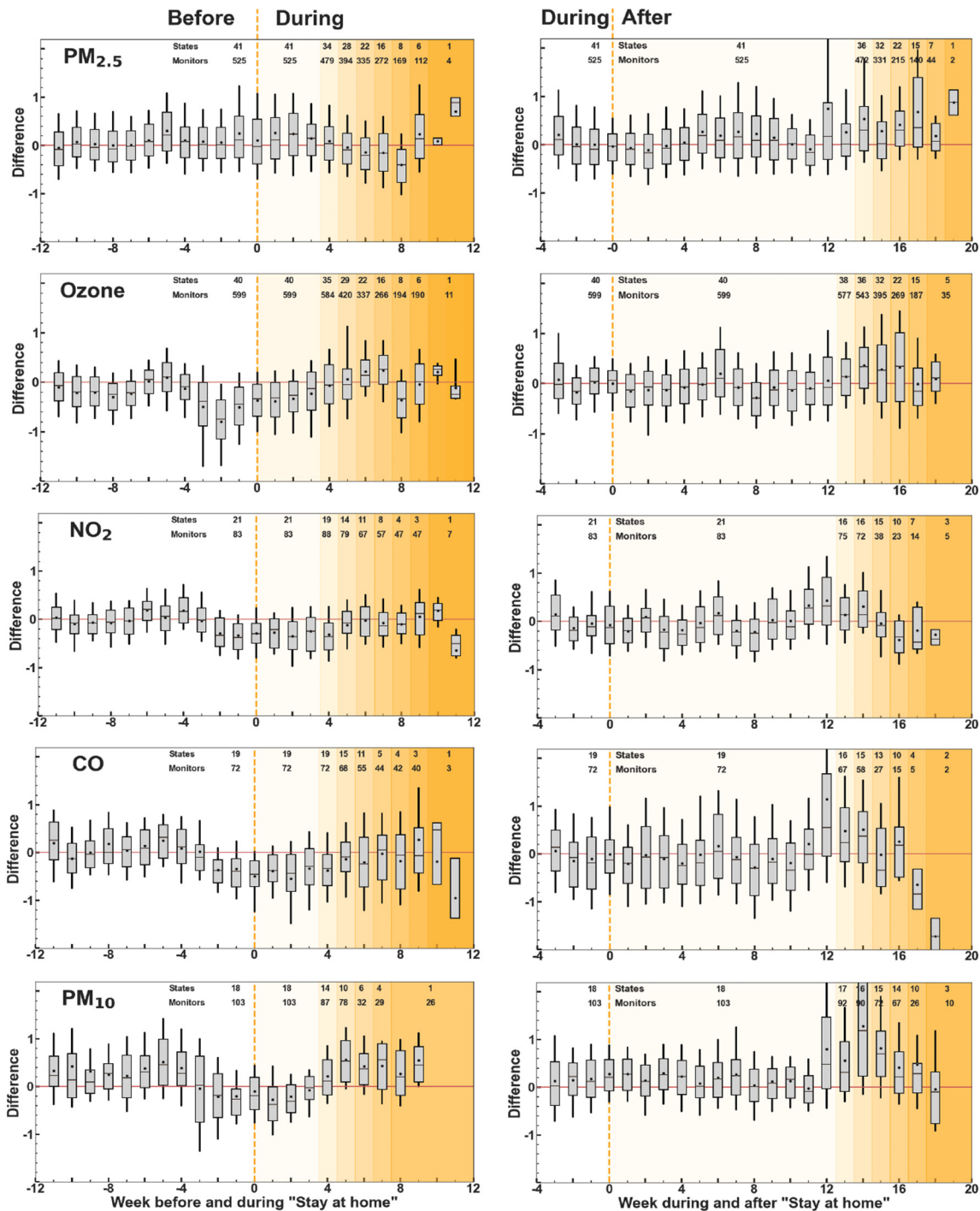


Fig. 2. Robust differences (Eq. (1)) between year-2020 and the long-term average for that week, for PM_{2.5}, ozone, NO₂, CO and PM₁₀ concentrations (top to bottom rows, respectively), with time adjusted to match each state's stay-at-home order. Left column: time = 0 reflects the day that stay-at-home started in that state. These plots compare before (time < 0) and during (time > 0) stay-at-home. Right column: time = 0 reflects the day that stay-at-home stopped in that state. These plots compare during (time < 0) and after (time > 0) stay-at-home. Numbers inset near the top of each panel indicate the number of states and monitors with data in that range: 41 states enacted stay-at-home orders 4 or more weeks prior to week #35 of the year (i.e., the last week for which we have data), 34 states enacted stay-at-home orders 5 or more weeks before week #35, and 28 states enacted stay-at-home orders 6 or more weeks before week #35 (see Table S1). The change in number of states included in the analysis is indicated via the yellow shading. The box-plots show 10th, 25th, 75th, and 90th percentiles, 50th percentile (horizontal line), and the mean (dot); these are summary statistics of monitors throughout the US.

concentrations around the time of the covid response, but not to the same degree as seen above at the EPA sites (Fig. S11). Overall, additional analyses will be needed to ascertain how much of 2020 ozone anomalies seen over the US are due to covid-related vs. transport effects. Our analysis suggests that the regional transport of ozone cannot fully explain the observed concentration patterns.

4. Discussion

Covid's overall impacts are terrible, causing death, disease, job loss, economic loss, stress, and isolation. The societal response to Covid has caused enormous economic changes, likely shifting patterns of activity by people, governments, schools, companies, and industrial facilities.

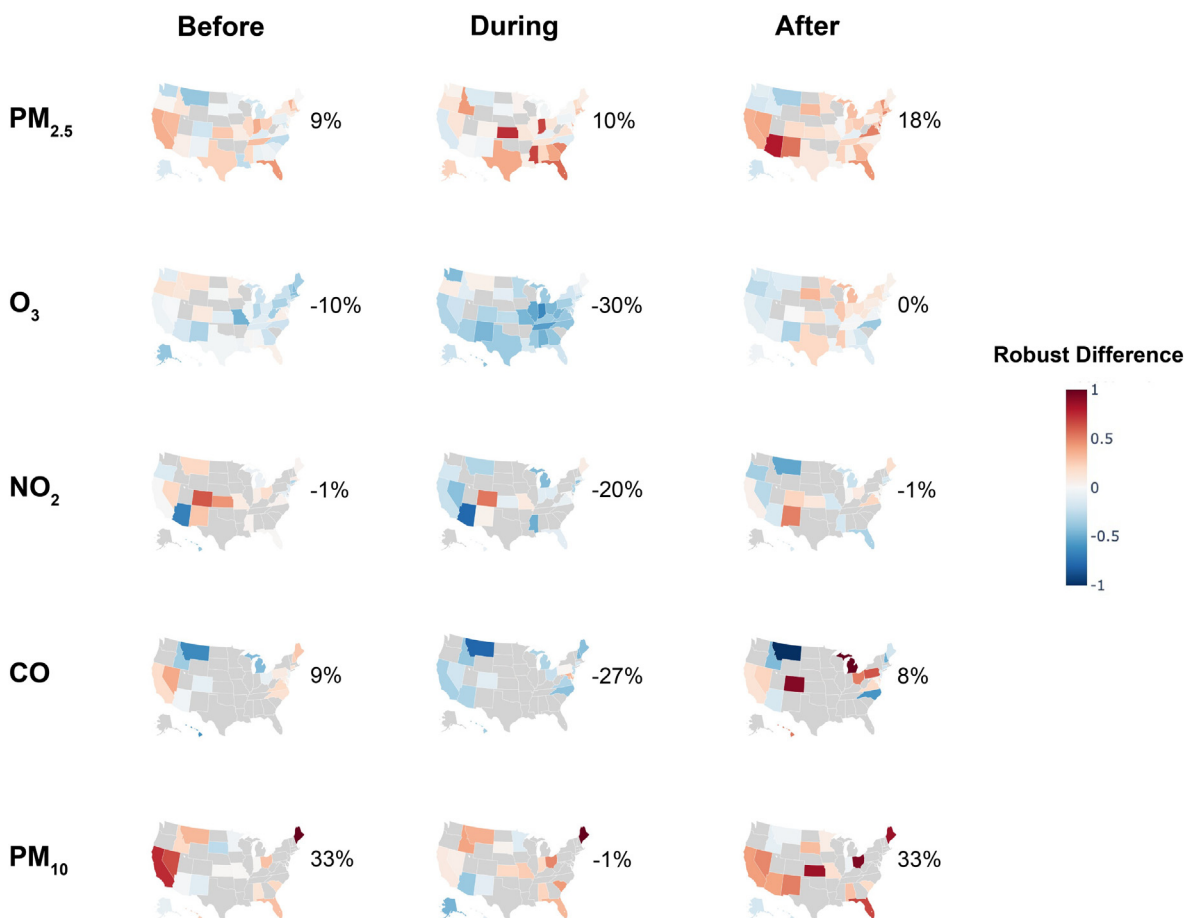


Fig. 3. Robust differences (see Eq. (1)) by state and pollutant. Here, “before” is the average of weeks 4 to 14 before that state’s stay-at-home order; “during” is the average of weeks 1 to 3 before and weeks 1 to 12 during that state’s stay-at-home order; and, “after” is the average of weeks 1 to 20 after the end of that state’s stay-at-home order. States shown in grey have no monitors that meet selection criteria and/or did not issue a stay-at-home order. The percentage numbers (right-side of each US map) indicate overall average robust differences (units: percentage of its IQR).

These changes create a unique opportunity to investigate the effects of human activity on air quality. To quantify these impacts, we analyzed criteria air pollution data from the EPA national monitoring network. We found that, during stay-at-home orders, levels of ozone, NO₂, CO, and PM₁₀ were lower than expected, but the anomaly was modest and temporary. (PM_{2.5} levels during stay-at-home orders were not lower-than-expected.) The decrease for ozone, NO₂, CO, and PM₁₀ started ~3 weeks prior to the stay-at-home order, and the anomaly lessened over time. Four weeks after the stay-at-home orders, PM₁₀ levels were at expected levels; five weeks after, ozone, NO₂ and CO levels were at expected levels (*p*>0.10). Most pollutants exhibited lower-than-expected levels of air pollution during the Covid response. However, the modest size of the drop (substantially less than one IQR;

i.e., a drop substantially less than typical year-to-year variability) and the fact that the drop was not sustained over time were both somewhat unexpected given the large reductions in social and economic activity implied by “stay-at-home” orders. PM_{2.5} did not exhibit a drop in pollution levels, which is another unexpected finding.

Air pollution concentrations depend on a complex mixture of sources, meteorology, and other factors. In order to isolate the effects of societal response Covid, one must control for non-Covid-response factors. We applied two methods to control for effects of seasonal and longer-term patterns and meteorology. The two approaches reveal broadly consistent conclusions. While our results reveal patterns and trends, they do not reveal causation nor regulatory impacts; additional research is needed to quantify the extent to which the observed changes

Table 1
Comparison of actual versus expected concentrations and D values before, during, and after stay-at-home orders.^a

Pollutant	Before (weeks -14 to -4)				During (weeks -3 to 12 of stay-at-home orders)				After (weeks +1 to +20 after the removal of stay-at-home orders)			
	Actual	Expected	Difference	D value	Actual	Expected	Difference	D value	Actual	Expected	Difference	D value
PM _{2.5}	7.04 µg/m ³	6.69 µg/m ³	5.1%	0.09	5.88 µg/m ³	5.58 µg/m ³	5.4%	0.10	7.42 µg/m ³	6.68 µg/m ³	10.0%	0.18
Ozone	34.79 ppb	35.54 ppb	-1.8%	-0.10	43.01 ppb	45.49 ppb	-5.3%	-0.30	43.62 ppb	43.82 ppb	-0.4%	0.00
NO ₂	25.11 ppb	25.13 ppb	-0.1%	-0.01	16.47 ppb	19.16 ppb	-14.0%	-0.20	14.83 ppb	14.99 ppb	-1.8%	-0.01
CO	0.55 ppm	0.51 ppm	7.4%	0.09	0.30 ppm	0.36 ppm	-15.3%	-0.27	0.31 ppm	0.30 ppm	3.7%	0.08
PM ₁₀	17.60 µg/m ³	14.83 µg/m ³	18.6%	0.32	17.27 µg/m ³	18.30 µg/m ³	-5.7%	-0.01	26.55 µg/m ³	22.66 µg/m ³	17.1%	0.33

^a “Expected concentrations” refer to the temporally-corrected historical medians; here, they are the means of the weekly medians. Example: actual year-2020 PM_{2.5} concentrations (units: µg/m³) are 7.04 before, 5.88 during, and 7.42 after, compared to expected concentrations of 6.69 before, 5.58 during, and 6.71 after; D values (unitless) are 0.09 before, 0.10 during, and 0.16 after. Those values indicate that before stay-at-home orders, year-2020 PM_{2.5} concentrations are 0.33 µg/m³ (5.1%) higher than expected, during stay-at home orders year-2020 concentrations are 0.30 µg/m³ (5.4%) higher than expected, and after stay-at-home orders year-2020 concentrations are 0.74 µg/m³ (10.0%) higher than expected.

are attributable to Covid-related changes (e.g., stay-at-home orders) versus other factors.

The results reveal important differences among pollutants. NO₂ and CO are primary (i.e., directly-emitted) pollutants; as a result, connections between changes in activity, emissions, and concentrations are relatively direct. In contrast, ambient PM_{2.5} includes both primary and secondary (forming in the atmosphere from chemical reactions) components. Ground-level ozone is secondary. For secondary pollutants, the connections between activity level, emissions, and concentrations are more complicated, and, as discussed below, reflect nonlinear atmospheric chemistry and emissions. Traffic is a major source of NO₂ and CO; in contrast, emissions from many sources contribute to levels of PM_{2.5}, PM₁₀, and ozone.

This paper adds to the emerging literature on the impacts of the Covid response on air quality by looking nationally, by analyzing available in-situ measurements for several criteria pollutants, by adjusting for random and nonrandom temporal variability (including, in the sensitivity analysis, explicitly adjusting for weather), and by analyzing before, during, and after “stay at home” orders. Our results are largely consistent with studies that examined wide-spread changes in the United States. For example, a study examining PM_{2.5} and NO₂ concentrations in 122 counties reported, for the US, a 25% decline in NO₂, and a statistically insignificant decline in PM_{2.5} compared to 2017–2019 levels (Berman and Ebisu, 2020). Another study found that in 20 US cities, after correcting for meteorology, NO₂ concentrations were 9%–43% lower than in 2019 (Goldberg et al., 2020). Analyses from individual locations, cities, or areas, can reveal different, potentially larger, impacts than the national-level trends are reported here. At a near-road monitoring station in Seattle, WA, concentrations of PM_{2.5}, NO₂ and CO during Covid were 2–4% lower than pre-Covid concentrations (Xiang et al., 2020). Data from a low-cost sensor network in Pittsburgh, PA, suggest that levels of PM_{2.5}, NO₂, and CO were 30–50% lower during than pre-Covid (Dantas et al., 2020).

Comparatively larger changes in air pollution have been reported in other countries. For example, in Barcelona, Spain, concentrations of NO₂ and black carbon were 50% lower during stay-at-home orders, but ozone concentrations increased by 50% (Tobias et al., 2020). In Delhi, India, measured concentrations of PM₁₀, PM_{2.5}, NO₂, and CO were substantially lower (for PM₁₀ and PM_{2.5}, ~2× lower) during shelter-in-place (Mahato and Ghosh, 2020). In three cities in China, PM_{2.5} and NO₂ levels in February 2020 were 30% and 61% lower than February 2017–2019 levels, respectively, but ozone levels were 14% higher than 2017–2019 levels (Xu et al., 2020). PM_{2.5} and ozone concentrations in the UK during April 2020 were not systematically different from average concentrations in 2015–2019, but NO₂ concentrations were 20–80% lower (Alfarra et al., 2020). In general, many of these studies did not fully account for random and systematic temporal variability, for multiple time-scales, as was done here.

Future research could usefully explore Covid-related changes in emissions or in atmospheric chemistry (Henneman et al., 2016; Seinfeld and Pandis, 2016; Thakrar et al., 2020), apply empirical modeling (e.g., national land use regression models) to understand spatial patterns in how pollution levels changed (Kim et al., 2020; Bechle et al., 2015; Novotny et al., 2011), analyze publicly-available networks of low-cost sensors such as PurpleAir (<https://www2.purpleair.com>; Feenstra et al., 2019; Malings et al., 2020), and investigate changes to existing inequalities in exposure to air pollution (Clark et al., 2014; Marshall, 2008; Clark et al., 2017).

The wide range in reported air quality changes associated with Covid responses around the world is not surprising. It provides an excellent example of the well-recognized complexity of the relationship between human activity, emissions, and ambient concentrations. There could be many reasons why we do not observe large, consistent, and sustained reductions in criteria air pollution levels across the US during stay-at-home orders, despite the enormous social and economic changes brought about by Covid.

First, there is substantial variability – random and systematic – which complicates finding a “signal” in changes in air pollution. We expect these effects would not completely hide large concentration changes, especially given the size of our dataset.

Second, ambient concentrations depend on the activity levels and emissions of many sources. Therefore, reducing emissions from one or a small number of source categories may or may not yield large change in concentrations. For example, while major reductions in vehicle traffic occurred in many locations due to “stay-at-home” orders, traffic is but one of many sources. In addition, stay-at-home orders could potentially increase some emissions (e.g., residential wood combustion, backyard BBQ cooking). Emissions can also 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).

Third, concentrations of secondary pollutants (e.g., ozone and a large portion of PM_{2.5}) depend on complex and nonlinear atmospheric chemistry, involving, especially, NO_x and volatile organic compound (VOC) emissions (Zhao et al., 2018). NO_x is a key player in the photochemical cycle that produces ozone and is a precursor for PM_{2.5} nitrate formation. For example, NO_x reacts with ozone; therefore higher NO_x emissions can lead to lower ozone concentrations near the emission source, especially in urban areas. The VOC:NO_x ratio influences the radical chemistry that produces ozone and secondary organic aerosol (a major component of PM_{2.5}). For example, increasing VOC:NO_x ratios can increase secondary organic aerosol yields, leading to increased PM_{2.5} concentrations (Chan et al., 2009; Li et al., 2015; Song et al., 2005; Ng et al., 2007). Finally, changing NO_x and VOCs emissions can alter hydroxyl radical concentrations, potentially leading to more rapid secondary PM and ozone production (Bahreini et al., 2012). This nonlinear chemistry creates multiple ways in which lower emissions can lead to higher secondary pollutant concentrations. An excellent example is the well-known weekend ozone effect, whereby lower traffic emissions cause higher weekend ozone levels (Marr and Harley, 2002). Similar phenomena may explain the increases in ozone concentration in response to Covid reported by some studies (Tobias et al., 2020; Mahato and Ghosh, 2020). Overall, the trends we observe are qualitatively consistent with known atmospheric chemistry.

Finally, the effects on air quality of societal responses to Covid may be lower in the US than in other countries, in part because of the comparatively cleaner air in the US (Apte et al., 2018; Goodkind et al., 2019). For example, because vehicle tailpipe emission factors are lower in the US than in many countries, reductions in driving, and the resulting reductions in tailpipe emissions, may have a smaller impact on air pollution levels for the US than for other countries.

5. Conclusion

We investigated how social and economic changes from Covid response, including stay-at-home orders, impacted levels of criteria air pollution, using data from hundreds of EPA monitoring stations across the US. We used two separate methods for deriving “expected” pollution levels (robust differences; regression). Both methods control for random and systematic variability on multiple time scales, by monitor-week, thereby providing an appropriate measure against which to compare observed pollution levels.

Results from both methods reveal that, during stay-at-home orders, average PM_{2.5} levels were higher than expected; average ozone, NO₂, CO, and PM₁₀ levels were slightly lower than expected. A small number of weeks after the stay-at-home orders were issued, the concentration anomalies ended; ozone, NO₂ and CO levels returned to expected levels and PM_{2.5} and PM₁₀ levels were higher than expected. In conclusion, PM_{2.5} levels have not dropped during or after stay-at-home orders;

ozone, NO₂, CO, and PM₁₀ concentrations dropped during stay-at-home orders but the reduction was modest and transient.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This research was funded by the National Science Foundation (Award #1737633) and US Environmental Protection Agency (Assistance Agreement #R835873; Center for Air, Climate, and Energy Solutions (CACES)). It has not been formally reviewed by the funders. The views expressed in this document are solely those of authors and do not necessarily reflect those of the funders. Funders do not endorse any products or commercial services mentioned in this publication. We gratefully acknowledge several organizations for making data publicly available, including the US Environmental Protection Agency (EPA), the US National Oceanic & Atmospheric Administration (NOAA), Carnegie Mellon University Environmental Sensor Data Repository (ESDR), and the European Center for Medium-Range Weather Forecasts (ECMWF). Adam Szpiro provided helpful guidance and suggestions on the regression models.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.scitotenv.2020.144693>.

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