

Decreases in Near-Road NO and NO₂ Concentrations during the COVID-19 Pandemic in California

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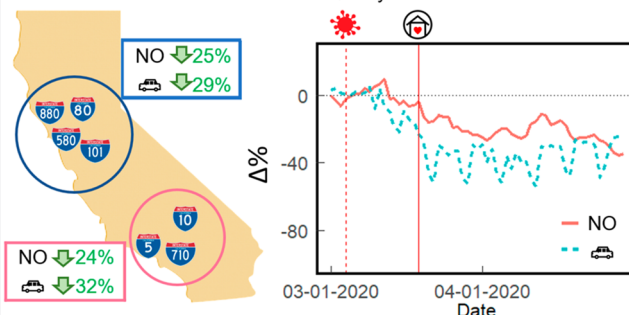
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Supporting Information

ABSTRACT: The COVID-19 pandemic and resulting shelter-in-place measures led to widespread adoption of remote work policies and temporary business closures or operation curtailments, disrupting typical commuting patterns. This study investigates how these sudden shifts in traffic patterns affected near-road NO and NO₂ concentrations in California. We used (1) near-road air pollution data from the U.S. Environmental Protection Agency's AirNow database, (2) passenger and heavy-duty traffic data from the Caltrans Performance Monitoring System, and (3) weather data from MesoWest between January 1 and April 30 during the years 2017–2020 to model NO and NO₂ concentrations as functions of highway traffic and meteorology. We then simulated NO and NO₂ under business-as-usual traffic conditions and compared modeled data to observed values. Weekday passenger traffic significantly declined in Northern and Southern California by 29% and 24%, respectively. As a result, Northern and Southern California near-road locations experienced statistically significant declines in NO concentrations of 35% and 32% and in NO₂ concentrations of 15% and 29%, respectively, compared to modeled estimates. As a natural experiment, our findings demonstrate that reduced vehicle activity significantly improved air quality, contributing to the body of evidence linking shelter-in-place measures and cleaner air.

Shelter-in-Place and Near-Road Air Quality



INTRODUCTION

In late 2019, the first outbreak of COVID-19 was detected in Wuhan, Hubei Province, China. The Chinese response included a lockdown of several cities and widespread social distancing measures. In California, the first confirmed cases were detected in late January 2020, with confirmed community spread soon thereafter. In March, many workplaces instituted remote work and government bodies issued regulations starting with a statewide emergency declaration on March 4, 2020. Local jurisdictions followed by banning public gatherings, and the state declared a shelter-in-place order on March 19, 2020.¹

As the COVID-19 pandemic spread, human activity halted under shelter-in-place measures. Many studies in China,^{2–17} India,^{18–26} Europe,^{27–29} South America,^{30–32} Central Asia,³³ and the United States^{21,34–37} have used satellite and stationary monitoring to demonstrate decreases in regional PM_{2.5} and NO₂ levels during shelter-in-place periods. While satellite data are widely available across the world, this approach has a few limitations. The target of many of these studies, NO₂, is a harmful secondary pollutant regulated by the Clean Air Act and a common tracer of vehicle activity.³⁸ In California, only 62% of net NO_x emissions, the sum of NO and NO₂ emissions, come from mobile sources, with the rest coming from cropland, fuel combustion, and miscellaneous sources.³⁹ Consequently, without quantifying changes in traffic, regional

studies can only implicitly link shelter-in-place measures to cleaner air. On the contrary, NO has not been linked to adverse health effects but is a more specific tracer of vehicle activity, directly generated by fuel combustion.⁴⁰ Once emitted, however, NO quickly oxidizes into NO₂, making it very responsive to sudden changes in highway traffic but difficult to measure outside of near-road monitoring networks.⁴¹ As a result, regional studies that do not measure traffic are limited in their ability to form causal conclusions between shelter-in-place measures and air pollution. We attempt to address this knowledge gap by focusing on traffic data and NO/NO₂ data from the U.S. Environmental Protection Agency's (EPA) near-road network, which explicitly measures mobile source air pollutants.

In California, the COVID-19 pandemic prompted a decline in economic activity and an unprecedented shift to remote work for many jobs, likely reducing the need for daily vehicle commuting and truck cargo traffic. Because (1) mobile sources

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contribute to more than half of all NO_x emissions in California,³⁹ (2) ~70% of gasoline and 80% of diesel traffic are on the highway system,⁴² and (3) NO is a tracer of vehicle traffic and a precursor to other air pollutants, changes in regional air pollution levels likely stem from changes in highway traffic and subsequent reductions in near-road NO concentrations. This study aims to relate pandemic-related traffic changes to near-road NO and NO₂ concentrations, accounting for potential seasonal and meteorological confounders and to separate the relative contributions of passenger versus truck traffic.

MATERIALS AND METHODS

Data Source. Our study draws data from January 1 to April 30, matching previous COVID-19 studies,^{43–45} for the years 2017–2020.

(1) Air quality data are sourced from AirNow, a database that reports hourly pollution and includes EPA's near-road network.⁴⁶ California has 13 EPA near-road pollution monitoring sites, of which seven had complete air pollution and traffic data available. Northern California had four sites, while Southern California had three, each targeting a different highway. Table S1 summarizes the name, county, and target road of each site, and Figures S1–S3 show the locations of each site. The most commonly available pollutants are NO and NO₂ concentrations (parts per billion), while other pollutants such as black carbon, PM_{2.5}, CO, and ozone are inconsistently reported. Fewer than half of the sites report meteorology data, which we used to validate more thorough meteorology data obtained from MesoWest.

(2) California traffic data are sourced from the Caltrans Performance Measurement System (PeMS), which reports traffic across all major metropolitan areas of the State of California.⁴⁷ We first downloaded daily traffic data from all traffic monitors within a 0.1, 0.25, and 1.0 mile radius of each near-road site. We then found that the 0.25 mile is the shortest distance that provides sufficient traffic data to allow us to calculate average traffic per site. Each vehicle detection system separately reports daily total passenger vehicles and trucks per day, defined by vehicle height, and percent observed—an indicator of completeness—for both measurements. For each traffic monitor, we downloaded the daily total number of passenger vehicles and trucks during our study period, selecting data that were ≥50% observed over the entire day.

(3) Weather data are sourced from MesoWest, a weather database run by the University of Utah.⁴⁸ For each near-road site, we downloaded temporally aligned data from the closest weather station, located between 2 and 11 miles away. Weather data included temperature, air pressure, relative humidity, wind speed, and type of precipitation reported at 5 min intervals.

We calculated daily statistics for AirNow data and MesoWest weather data to match PeMS traffic data, which report daily total flow. We calculated daily averages for NO and NO₂ concentrations, traffic data, wind speed, relative humidity, and atmospheric pressure. We calculated daily minimum for air temperature, based on findings from a previous study.⁴⁹ We coded precipitation as a dichotomous variable (1 for any precipitation, 0 for none). In our final data set, our data points could be identified by their date (month, day, year) and location.

Data Analysis and Model Development. We began with exploratory data analysis, including univariate plots, summary statistics, and correlation analysis. To account for

nonlinear relationships, we applied generalized additive models (GAM), often used in air pollution research.^{3,50,51} We generated our models with a forward selection process, beginning with traffic variables and individually adding meteorology covariates. We kept variables if they substantially improved the model fit and accuracy as determined by AIC and adjusted R².² For each variable, we chose either a linear or a smoothing component by calculating the estimated degrees of freedom (EDF) and the statistical significance of the GAM smoother as well as by plotting the variable in question against dependent variables across each location. During this process, we considered a variable with an EDF of ≥2 to be nonlinear.

Due to spatial and temporal variations in vehicle fleet composition, we assumed emissions per vehicle differed at each location–year combination.⁵² Additionally, because Northern and Southern California have different climates, we divided our sites accordingly and included a region variable that interacts multiplicatively with our meteorology variables.⁵³

The dependent variables are daily average NO (parts per billion) and NO₂ (parts per billion). We selected the following independent variables: year and location, region, passenger traffic and truck traffic by year and location (vehicles per day), daily average wind speed (miles per hour) by region, precipitation by region (1 if any precipitation, 0 if none), daily average relative humidity (percent) by region, daily average atmospheric pressure (pascals) by region, and daily minimum temperature (degrees Celsius) by region.

Exploratory analysis revealed that traffic related linearly to NO and NO₂ concentrations at all sites except Long Beach and Ontario Etiwanda (EDF > 1). For those two sites, we predicted NO and NO₂ concentrations with a model that treats traffic nonparametrically (eq 1), with other sites using a linear term with traffic (eq 2). Our models are as follows:

$$E(Y_d) = \alpha + yr_L + R + \beta(Z_{1,R}) + s(Z_{2,R}) + s(T_{yr,L}) \quad (1)$$

$$E(Y_d) = \alpha + yr_L + R + \beta(Z_{1,R}) + s(Z_{2,R}) + \beta(T_{yr,L}) \quad (2)$$

where Y_d is the NO or NO₂ concentration on a given day d , α is a constant, β refers to a regression coefficient, R is a dummy variable denoting region, yr_L is a dummy variable denoting yearly differences at each location L , $Z_{1,R}$ is a set of meteorology variables found to have a linear relationship with the outcome at region R , $Z_{2,R}$ refers to the remaining meteorology variables, $T_{yr,L}$ refers to the effect of traffic variables at each location L during a given year yr , and s is the smoothing nonparametric spline function.

Model Validation. We used the K-fold cross-validation method with 10 folds to assess our models. We randomly assigned the data into 80% training, 20% testing and calculated the adjusted R², repeating the procedure 10 times to derive a mean R² of our CV results. Our mean adjusted R² values for NO were 0.66 with linear terms for traffic and 0.68 with a nonparametric smoother. For NO₂, our adjusted R² values were 0.78 with linear terms for traffic and 0.81 with a nonparametric smoother. This suggests a strong fit for both dependent variables that matches the performance of prior studies,⁵⁰ though we did find that our models slightly underestimated mobile source emissions.

Simulating Traffic and NO and NO₂. We simulated a business-as-usual scenario by assuming that without the COVID-19 pandemic, passenger and truck traffic would

Table 1. Percent Reductions in Vehicle Flow and NO Emissions between Observed Measurements and Simulated Business-as-Usual Measurements from March 1 to April 30, 2020^a

Region or Site	% passenger flow reduction (SD)		% truck flow reduction (SD)		% NO concentration reduction (SD)		% NO ₂ concentration reduction (SD)	
	Weekday (N = 44)	Weekend (N = 17)	Weekday (N = 44)	Weekend (N = 17)	Weekday (N = 44)	Weekend (N = 17)	Weekday (N = 44)	Weekend (N = 17)
Northern California	29 (17) ^b	42 (23) ^b	23 (14) ^b	44 (20) ^b	35 (5.1) ^b	60 (2) ^b	29 (7.3) ^b	44 (0.87) ^b
Berkeley Aquatic Park	23 (15) ^b	38 (23) ^b	13 (10) ^b	34 (21) ^b	26 (4.6) ^b	22 (13) ^b	19 (4.2) ^b	26 (0.96) ^b
Knox Avenue	31 (19) ^b	42 (23) ^b	37 (16) ^b	53 (20) ^b	44 (6.2) ^b	43 (20) ^b	39 (9.6) ^b	54 (1.4) ^b
Laney College	29 (14) ^b	40 (25) ^b	22 (5.4) ^b	43 (9.4) ^b	42 (8.5) ^b	33 (21) ^b	31 (6.8) ^b	45 (0.85) ^b
Owens Court	34 (19) ^b	47 (25) ^b	20 (12) ^b	48 (24) ^b	30 (10) ^b	25 (23) ^b	26 (9.4) ^b	49 (1.1) ^b
Southern California	24 (15) ^b	37 (20) ^b	4 (9.3)	21 (15)	32 (9.3) ^b	20 (6.8) ^b	15 (5.8) ^b	31 (3.6) ^b
Anaheim Route 5 Near Road	31 (18) ^b	41 (21) ^b	3 (13)	16 (14) ^b	−11 (9.2) ^b	−15 (20)	21 (5.3) ^b	45 (0.99) ^b
Long Beach Route 710 Near Road	22 (12) ^b	37 (19) ^b	7 (6.1) ^b	34 (12) ^b	47 (8.5) ^b	40 (16) ^b	15 (6.4) ^b	29 (1.5) ^b
Ontario Etiwanda Near Road	19 (11) ^b	34 (20) ^b	2 (6.7)	13 (11) ^b	28 (13) ^b	19 (17) ^b	10 (10) ^b	22 (9.2) ^b

^aData are separated by site and overall region as well as weekdays and weekends. Standard deviations (SD) of percentage reductions are given in parentheses. ^bStatistical significance from a null value of 0 or no change ($p < 0.05$) using the Welch's t test.

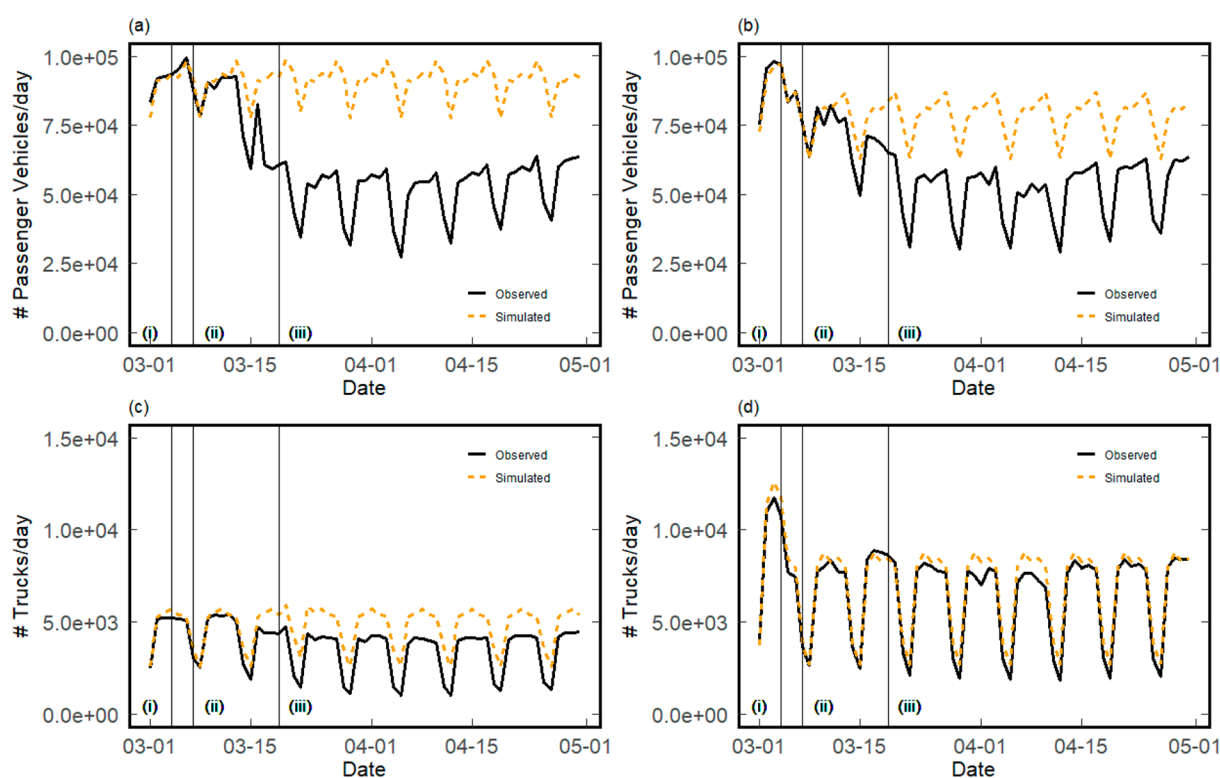


Figure 1. Observed (black solid line) vs business-as-usual (yellow dotted line) traffic flow in California from March 1 to April 30, 2020. (a) Northern California passenger vehicle traffic, (b) Southern California passenger vehicle traffic, (c) Northern California truck traffic, and (d) Southern California truck traffic. The three vertical lines represent (i) March 3, when California declared a state of emergency, (ii) March 7, when the city of San Francisco banned large group gatherings, and (iii) when California declared a statewide shelter-in-place order, from left to right, respectively.

exhibit weekly patterns identical to those in the months of January and February 2020 and those in March and April from 2017 to 2019. Traffic levels were similar between the two sets, but the interyear variation between the same months was greater than the intermonth variation within the same year at most sites (see Table S2). This led us to simulate passenger and truck traffic using data from January and February 2020, which represents a more accurate estimate, as a business-as-usual scenario. Days between March 1 and April 30, matching previous studies,^{43–45} were assigned a passenger and truck flow

value equivalent to the weekday average of each day during the first two months of the year. For example, Mondays had traffic measurements equivalent to the average Monday traffic in January and February. We calculated the change in traffic with the following equation:

$$\text{percent change in traffic} = \frac{\text{simulated traffic} - \text{observed traffic}}{\text{simulated traffic}} \times 100 \quad (3)$$

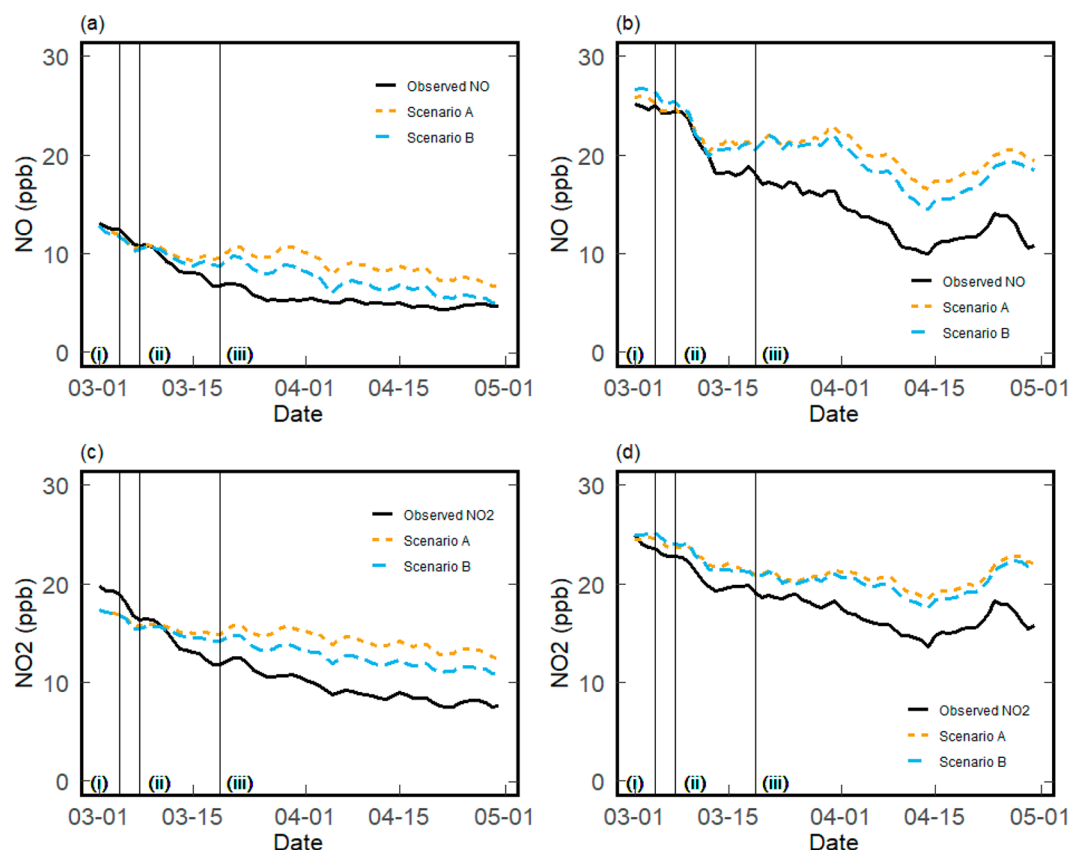


Figure 2. Two-week rolling averages of observed near-road NO and NO₂ concentrations vs simulated scenarios in California: (a) Northern California NO, (b) Southern California NO, (c) Northern California NO₂, and (d) Southern California NO₂. The black solid line is observed data. The yellow dotted line depicts predicted NO and NO₂ concentrations under scenario A, simulated business-as-usual passenger flow and truck flow. The blue dashed line depicts predicted NO and NO₂ concentrations under scenario B, simulated business-as-usual passenger and observed truck flow. The three vertical lines represent (i) March 3, when California declared a state of emergency, (ii) March 7, when the city of San Francisco banned large group gatherings, and (iii) when California declared a statewide shelter-in-place order, from left to right, respectively.

On the basis of simulated business-as-usual traffic values, we used our GAMs (eqs 1 and 2) to predict NO and NO₂ concentrations during the months of March and April under two scenarios. Scenario A predicts NO and NO₂ concentrations with business-as-usual simulated passenger and truck traffic. Scenario B predicts with business-as-usual simulated passenger traffic and observed truck traffic data. The difference between the two scenarios illustrates the relative contribution of the decline in passenger vehicles to the overall reduction of NO and NO₂ concentrations. We then used Welch two-sample *t* tests to assess the statistical significance of the differences between the observed and predicted traffic, NO and NO₂ measurements on weekdays and weekends. In Table 1, significant differences as indicated by the Welch's *t* test are marked with an asterisk. We used the following equation to calculate the percent change in NO:

$$\text{percent change in NO or NO}_2 = \frac{\text{simulated} - \text{observed}}{\text{simulated}} \times 100 \quad (4)$$

We used R version 3.6.3⁵⁴ to conduct data retrieval, analysis, and visualization in this study.

RESULTS AND DISCUSSION

Changes in Vehicle Flow. Figure 1 depicts passenger vehicle and truck traffic in Northern and Southern California between March 1 and April 30. Panels a and b of Figure 1

depict a substantial decline in passenger traffic beginning in early March, reflecting the massive shift to remote work. Panels c and d of Figure 1 show that truck flow, a possible indicator of commercial activity, decreased in Northern, but not Southern California. Table 1 quantifies these observations by location and splits the data into weekdays and weekends. We find percent declines in traffic during both weekdays and weekends. The former likely indicates declines in commuting, and the latter likely indicates declines in noncommuting activity, such as recreational activities and traveling. Passenger traffic declined in Northern and Southern California, by 29% and 24% on weekdays and 42% and 37% on weekends, respectively. Weekday truck flow decreased by 13–37% in Northern California locations and 2–7% in Southern California locations with varying degrees of statistical significance, marked by an asterisk, suggesting that during the weekdays, the flow of goods did not change as much as in the north. Similarly, on weekends, we noticed a 44% decline in truck traffic in Northern California, compared to 21% in Southern California, which was not statistically significant.

Changes in NO and NO₂ Concentrations. Figure 2 depicts 14-day rolling averages of NO and NO₂ levels in Northern and Southern California. The black solid line represents observed data, while the yellow dashed line depicts predicted NO and NO₂ concentrations under scenario A, which simulates business-as-usual truck and passenger vehicle traffic. The blue dashed line represents predicted NO and NO₂

concentrations under scenario B, simulating business-as-usual passenger traffic only. We find that a greater share of NO and NO₂ reductions can be attributed to passenger traffic decline in Southern California, shown by a smaller gap between blue and yellow lines, due to smaller, insignificant changes in the region's truck flow.

As shown in Table 1, NO concentrations fell by 35% and 60% on weekdays and weekends, respectively, in Northern California and by 32% and 20% on weekdays and weekends, respectively, in Southern California. Our results agree with previous COVID-19-related studies that have reported NO₂ emission reductions in California.^{43–45} Outside of California, studies around the world have also found a consistent decline in NO₂ concentrations.^{2–37} While traffic reductions of this scale are historically unprecedented, other smaller scale natural experiments that disrupt automobile traffic, such as a major highway closure,⁴¹ major sporting events,^{55–57} and odd–even license plate traffic policies,⁵⁸ have produced similar declines in direction and magnitude in air pollution following declines in traffic. Our results confirm and reinforce the relationship between traffic and mobile source pollution.

Our analysis has a few limitations. We ended our study period on April 30 to focus on the most stringent shelter-in-place period and match previous studies. As a result, we could not observe how scattered opening up of California localities affected traffic and air quality, which warrants further studies. With regard to our data sources and methodology, a cutoff of 50% observed traffic may lead to an excess of algorithmically generated data that ignore immediate pandemic-related traffic impacts. As a result, we may be overestimating traffic flow and underestimating NO and NO₂ concentration reductions. Another limitation is related to the uncertainty of traffic and pollution estimates. While we did not quantify these uncertainties, we found that traffic changed very little during January and February 2020 (mean coefficient of variation of 11%). Due to the low coefficient of variation, large effect size, and statistical significance of the results, we do not expect such uncertainties would alter our conclusions. Lastly, another source of bias may arise from weather data. Fewer than half of the EPA near-road sites in California reported meteorology data, necessitating the use of a different data source. Nevertheless, meteorology data reported by near-road sites were very highly correlated with MesoWest data, with correlation coefficients between sources of temperature, relative humidity, and wind speed data of 0.97, 0.95, and 0.75, respectively. In addition, the data fit well on the basis of adjusted R² values, suggesting a robust model.

In summary, we estimated the meteorology-adjusted decline in NO and NO₂ concentrations that can be attributed to quantified changes in near-road traffic following shelter-in-place measures in California. We found that the contribution of declines in passenger versus truck traffic to changes in NO and NO₂ concentrations differs between Northern and Southern California. We report one of the first studies that quantifies the effect of directly measured traffic on NO and NO₂ concentration reduction, the former being a significant precursor to the latter as well as other mobile source-derived pollutants, including ozone, PM_{2.5}, and smog. This paper shows a directly measured link between reduced traffic and reduced NO and NO₂ emissions, strengthening the evidence base among COVID-19, shelter-in-place measures, and cleaner air.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at <https://pubs.acs.org/doi/10.1021/acs.estlett.0c00815>.

List and of near-road monitoring sites, with the county and targeted highway (Table S1); map showing the locations of near-road monitoring sites in California (Figure S1) as well as in Northern and Southern California (Figures S2 and S3, respectively); and mean standard deviations of passenger and truck flow for within-month traffic between 2017 and 2019 and within-year traffic between January and April within the same year for the years 2017–2019 (Table S2) (PDF)

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Notes

The authors declare no competing financial interest.

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