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Research Report

Air pollution benefits from reduced on-road activity due to COVID-19 in the United States

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Abstract

On-road transportation is one of the largest contributors to air pollution in the United States. The COVID-19 pandemic provided the unintended experiment of reduced on-road emissions' impacts on air pollution due to lockdowns across the United States. Studies have quantified on-road transportation's impact on fine particulate matter ($PM_{2.5}$)–attributable and ozone (O_3)–attributable adverse health outcomes in the United States, and other studies have quantified air pollution–attributable health outcome reductions due to COVID-19-related lockdowns. We aim to quantify the $PM_{2.5}$-attributable, O_3-attributable, and nitrogen dioxide (NO_2)–attributable adverse health outcomes from traffic emissions as well as the air pollution benefits due to reduced on-road activity during the pandemic in 2020. We estimate 79,400 (95% CI 46,100–121,000) premature mortalities each year due to on-road-attributable $PM_{2.5}$, O_3, and NO_2. We further break down the impacts by pollutant and vehicle types (passenger [PAS] vs. freight [FRT] vehicles). We estimate PAS vehicles to be responsible for 63% of total impacts and FRT vehicles 37%. Nitrogen oxide (NO_X) emissions from these vehicles are responsible for 78% of total impacts as it is a precursor for $PM_{2.5}$ and O_3. Utilizing annual vehicle miles traveled reductions in 2020, we estimate that 9,300 (5,500–14,000) deaths from air pollution were avoided in 2020 due to the state-specific reductions in on-road activity across the continental United States. By quantifying the air pollution public health benefits from lockdown-related reductions in on-road emissions, the results from this study stress the need for continued emission mitigation policies, like the U.S. Environmental Protection Agency's (EPA) recently proposed NO_X standards for heavy-duty vehicles, to mitigate on-road transportation's public health impact.

Keywords: air quality, COVID-19, transportation, public health

Significance Statement

On-road transportation emissions are one of the largest contributors to air quality–related health outcomes in the United States. Most studies quantifying their impacts have only considered exposure to fine particulate matter ($PM_{2.5}$) and ozone (O_3). We assess exposure to on-road-attributable $PM_{2.5}$, O_3, and nitrogen dioxide and estimate 79,400 (46,100 to 121,000) premature mortalities that occur each year. We also assess the air quality–related health impacts from reduced on-road transportation during the COVID-19 pandemic in 2020 and estimate that 9,300 (5,500 to 14,000) deaths from air pollution were avoided due to pandemic-related lockdowns. The pandemic-related reductions show the continued importance of on-road emission mitigation strategies for improving public health in the United States.

Introduction

In the United States, road transportation emissions have been estimated to be the largest source of fine particulate matter–related ($PM_{2.5}$) and ozone-related (O_3) premature mortalities (1). Recent studies estimate that roughly 17,000 to 20,000 deaths occur each year from road transportation pollution (2–6). Recently, the transportation-related health burden attributable to nitrogen dioxide (NO_2) has been gaining attention (7–12). While evidence from toxicological studies is still growing (7–9, 13, 14) to support the causality of mortality to long-term exposure to ambient NO_2, the World Health Organization recently updated its targets for annual NO_2 concentrations (15), and the US Environmental Protection Agency is currently updating its Integrated Science Assessment for Oxides of Nitrogen-Health Criteria (16).

Road transportation emissions were reduced as a result of lockdowns due to the COVID-19 pandemic in 2020 with significant reductions measured in the United States (17, 18), China (19), India (20), Japan (21), and Western Europe (22). These reductions in emissions led to pronounced reductions in ambient air pollutant

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concentrations of NO_2 (20, 23–32), $PM_{2.5}$ (20, 23, 25, 29–31, 33), and a mixed response for O_3 (27, 29, 31, 34).

Impacts from road transportation in the United States vary by vehicle and fuel types, emitted pollutants, and source regions (3, 35). As a result of state-specific lockdown protocols and altered vehicle usage during the COVID-19 pandemic, emission changes from vehicle types and regions of the country varied (17, 26, 36). While studies have attempted to quantify the impact of air pollution changes due to the pandemic from ambient measurement and remote-sensing data (37–39), quantifying the impacts due to road transportation reductions through modeling efforts is difficult as official emission inventories representative of those varied responses in 2020 are not yet available.

This study estimates the total health burden in the United States from exposure to road transportation–attributable concentrations of $PM_{2.5}$, O_3, and NO_2. We break down the impacts by vehicle classes, emissions precursors, and source states. We utilize chemistry transport model–derived sensitivities of $PM_{2.5}$, O_3, and NO_2 to passenger (PAS) and freight (FRT) vehicles' emissions of nitrogen oxides (NO_X), volatile organic compounds (VOCs), sulfur dioxide (SO_2), ammonia (NH_3), and primary fine particulate matter (PPM) from each state. Sensitivities are at a 12-km resolution for the entire continental United States, and emissions are from the 2016 National Emissions Inventory (NEI). Health impacts are estimated by combining county-level mortality data and pollutant-specific concentration response functions (CRFs). We utilize the sensitivities to scale emissions by each vehicle class from each state by the activity changes observed during 2020 to estimate the changes to pollutant concentrations and attributable health burdens as a result of those activity changes. By utilizing one of the most recent emission inventories (the 2017 NEI was released after the modeling for this study had been performed), we are estimating how COVID-19 lockdowns in the United States impacted air quality and related health outcomes in 2020.

Results

US health impacts

We estimate the total on-road-attributable air pollution health burden—the sum of mortalities from exposure to on-road-attributable $PM_{2.5}$, O_3, and NO_2—to be 79,400 (95% CI 46,100–121,000) in the United States in 2016. This equates to monetary damages of \$820 billion (\$280–1,800). We estimate 24% of the \$820 billion is from $PM_{2.5}$ exposure, 20% from O_3, and 56% from NO_2. With regard to vehicle class, we estimate PAS vehicles to be responsible for 63% of total damages and FRT vehicles 37%. NO_X emissions from these vehicles are responsible for most damages (78%) as it is a precursor for $PM_{2.5}$ and O_3. PPM emissions are responsible for the second most damage (12%). VOC, NH_3, and SO_2 make up the remaining 10%. Figure 1 shows the total premature mortalities in the United States from on-road transportation by vehicle class, emission precursor, and pollutant (Table S3 shows the valuation amounts). We can also quantify the contributions to the US totals from each of these variables by source state. We estimate that on-road emissions from California, Florida, Illinois, New Jersey, New York, Ohio, Pennsylvania, and Texas are responsible for ~50% of total damages in the United States.

We also quantify the on-road-attributable premature mortalities occurring in each state. Figure 2 shows the total ($PM_{2.5} + O_3 + NO_2$) premature mortalities in each state. We estimate California to be the most impacted by on-road-attributable air pollution with 11,000 (6,800–16,000) premature mortalities. New York (6,100 [3,600–9,100]) and Florida (5,700 [3,200–8,600]) experience the second and third most impacts, respectively (Table S4 shows the values for all states).

Impacts in each state can be further broken down by pollutant, vehicle class, and emission precursor. Figure 3A (Table S5) shows the percentage of premature mortalities in each state due to on-road-attributable $PM_{2.5}$, O_3, and NO_2. Western states such as California, Oregon, Nevada, Utah, and Washington have >70% of their total impacts from NO_2 due to the lack of regional downwind transport of emissions that contribute to $PM_{2.5}$ and O_3. Half of the states considered have >50% of their total impacts from NO_2. Impacts from $PM_{2.5}$ ranged from 13 to 34% and impacts from O_3 ranged from 1 to 47% of the total impacts in each state.

Figure 3B (Table S7) shows the percentage of premature mortalities in each state due to emissions from the two vehicle classes we considered, PAS and FRT vehicles. North Dakota and Utah are the only two states to have a majority of their impacts from FRT emissions. Colorado, Oregon, North Carolina, Connecticut, Virginia, and Montana have >70% of their total impacts from PAS emissions. The remaining states' impacts from PAS emissions range from 52 to 69%.

Last, Figure 3C (Table S6) shows the percentage of premature mortalities in each state due to precursor emissions of NO_X, PPM, VOCs, NH_3, and SO_2. Similar to total damages in the United States, NO_X emissions are responsible for the most impact with >70% of impacts in each state. PPM emissions are responsible for the second most impact in each state except for Arkansas, Iowa, Mississippi, Vermont, and West Virginia, where VOC emissions are responsible for the second most impact.

Impacts due to COVID-19

The pandemic in 2020 resulted in significant decreases in on-road transportation activity in the United States. We utilize vehicle miles traveled (VMT) data representative of the reductions observed during 2020 when compared with "prepandemic levels" for each state and vehicle class. Figure S1 shows the annual percent changes in VMT for PAS and FRT vehicles in each state. With regard to PAS activity, average VMT reductions in the United States were ~17%. Approximately 39% of states experienced >20% reductions in PAS VMT. Michigan, Rhode Island, Maine, Massachusetts, North Dakota, Montana, and the District of Columbia experienced >25% reductions. US average FRT VMT reductions were smaller than PAS at ~5%. Only Maine, Vermont, and North Dakota saw reductions >10%, while Delaware and the District of Columbia experienced a 2 and 8% increase in FRT VMT, respectively. Vermont was the only state to experience larger reductions in FRT VMT than PAS VMT.

Those percent changes are used to scale the air pollutant sensitivities with respect to source state, vehicle class, and precursor emissions. For this analysis, we assume VMT changes to be equivalent to emission changes. We estimate that 9,300 (5,500–14,000) deaths from air pollution were avoided in 2020 due to the reductions in on-road activity across the continental United States. This equates to an economic benefit of \$96 billion (\$34–200). We estimate that changes in PAS activity resulted in 8,100 (4,700–12,000) deaths avoided (86% of total benefits), and changes in FRT activity resulted in 1,300 (730–1,900) deaths avoided (14% of total benefits). NO_2 reductions were responsible for 55% of benefits, $PM_{2.5}$ for 25%, and O_3 for 20%.

Figure 4 (Tables S8 and S9) shows the $PM_{2.5}$-related, O_3-related, and NO_2-related premature mortalities due to annual PAS and FRT VMT changes as a result of the pandemic in each state. For PAS activity changes, premature mortalities avoided due to NO_2

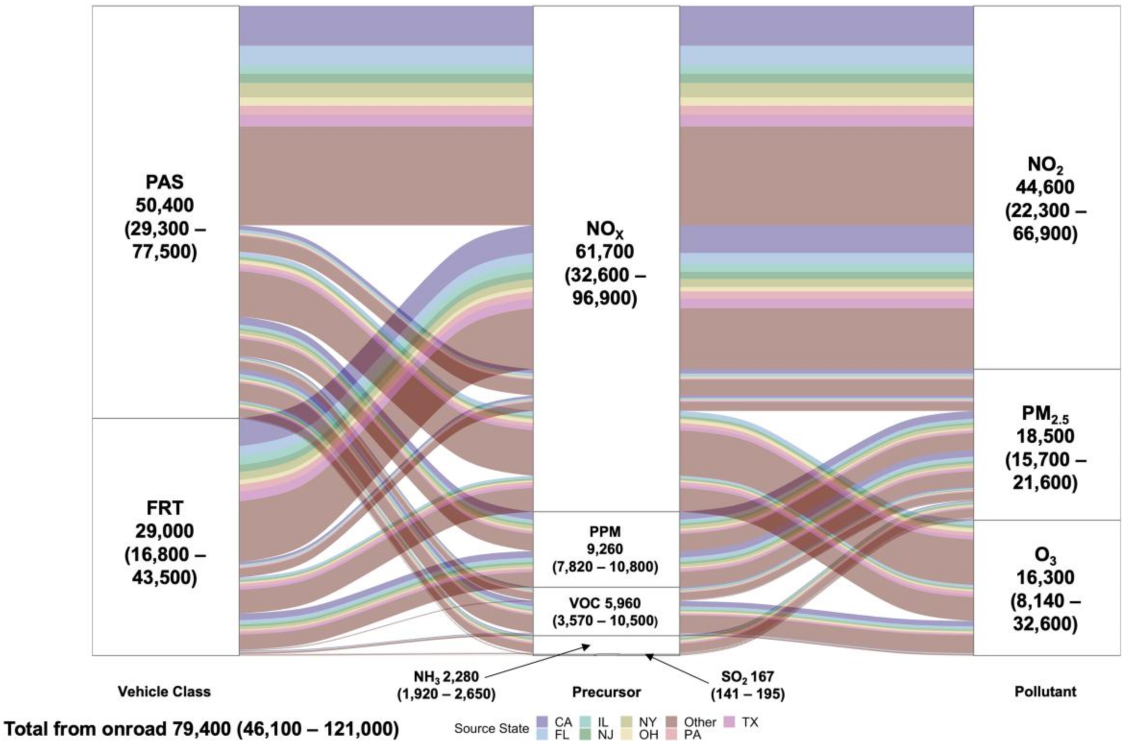

Fig. 1. Total on-road-attributable premature mortalities in the United States by vehicle class, emission precursor, and pollutant.

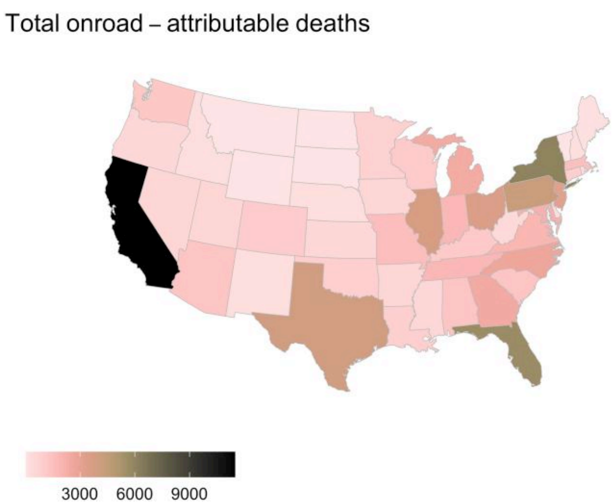

Fig. 2. Total on-road-attributable premature mortalities in each state.

and $PM_{2.5}$ changes are greatest in California; for premature mortalities due to O_3 changes, New York has the most reductions. For FRT activity changes, premature mortalities avoided due to NO_2 changes are greatest in Texas, to $PM_{2.5}$ in California, and to O_3 in Pennsylvania. For the case of FRT changes, California and Washington experienced a small increase (four and one premature deaths incurred, respectively) from O_3 changes likely from NO titration effects commonly observed in VOC-limited photochemical regimes (40).

Figure S2 shows the percentages of premature mortalities avoided due to changes in activity from the state itself. Percentages of source states' impact for $PM_{2.5}$ changes range from 7 to 98% in the cases of PAS and FRT activity changes, except for the District of Columbia and Delaware where an increase in FRT activity leads to the source state's impact inversely affecting the overall change in premature mortalities in the state. Percentages for O_3 changes range from 1 to 78% in the case of PAS activity changes, except for the District of Columbia's, Nevada's, and Utah's PAS reductions inversely impacting O_3 through NO titrations. In the case of FRT activity changes, percentages for O_3 changes range from 0.4 to 73%. O_3 titration effects were seen for source state FRT changes in Utah, Nevada, Oregon, Colorado, Rhode Island, Delaware, Washington, and California. Percentages for NO_2 changes range from 21 to 100% in the cases of PAS and FRT activity changes, except for FRT changes in the District of Columbia and Delaware similar to the $PM_{2.5}$ source state impacts.

Figure S3 shows the distribution of the percentages of premature mortalities avoided due to changes in activity from the state itself for the three pollutants. The distributions can tell us whether changes in a source state tend to impact pollutant concentrations regionally (impacts are largely outside the source state) or locally (impacts are largely inside the source state). We can see that changes in a source state tend to impact O_3 concentrations regionally and NO_2 concentrations locally. $PM_{2.5}$ distributions are wider, which indicates both regional and local impacts due to source state changes.

Discussion

Here, we estimate the on-road-attributable $PM_{2.5}$, O_3, and NO_2 premature mortalities in the United States by vehicle class, precursor, and pollutant. We also estimate the reductions in air pollution mortalities from road transportation activity changes due to lockdowns from the COVID-19 pandemic. To the authors' knowledge, this is the only study to (i) quantify the on-road-attributable NO_2 health impacts in the United States

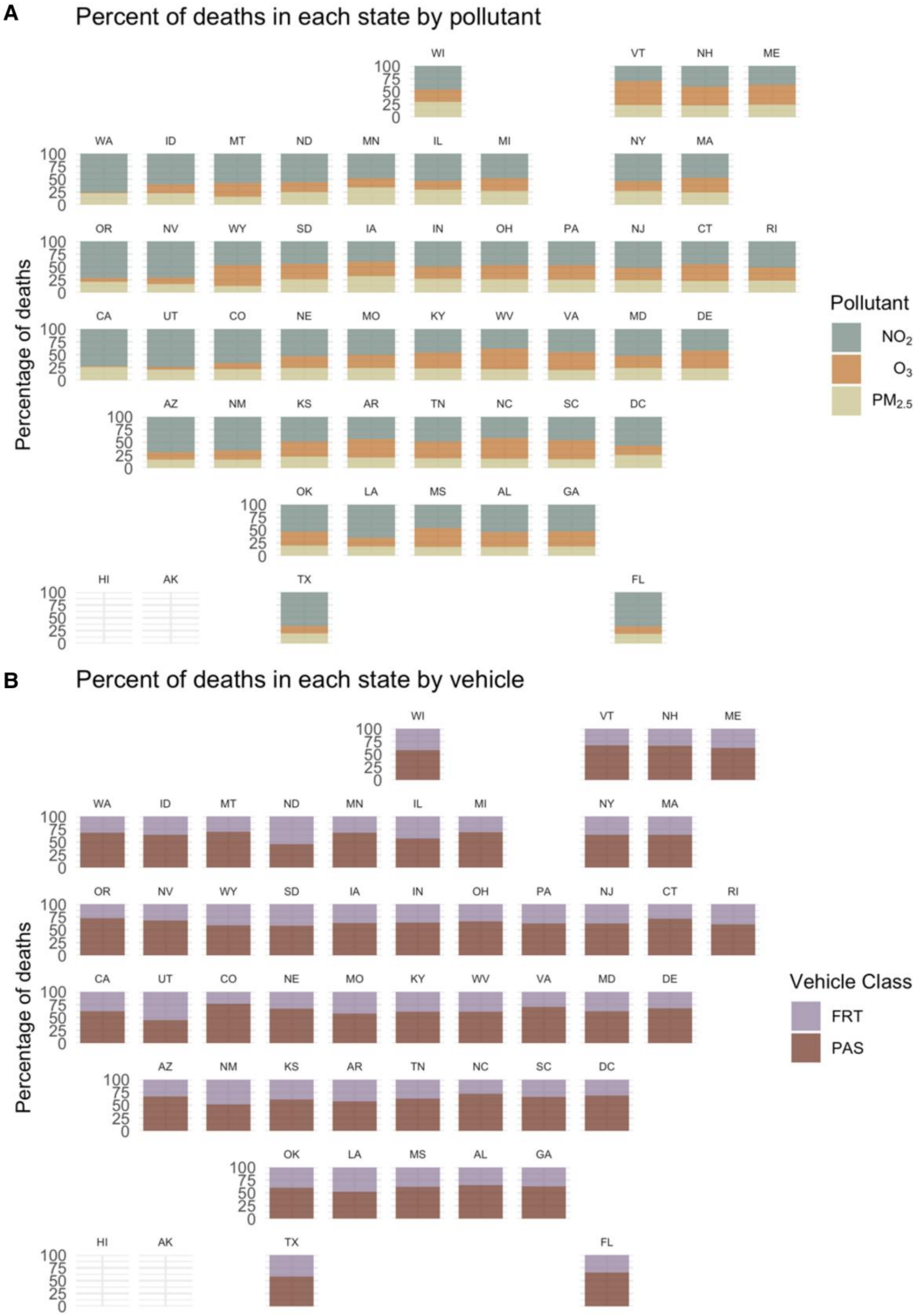

Fig. 3. Percentage of premature mortalities in each state due to (A) pollutant, (B) vehicle class, and (C) precursor.

and (ii) quantify the air pollution benefits from annual decreased road transportation due to the pandemic in the United States.

Comparing baseline $PM_{2.5}$ health impacts, our estimate of 18,500 premature mortalities in 2016 compares well with other modeling studies for similar years. Choma et al. (2) estimated 19,800 premature mortalities in 2017, Dedoussi et al. (3) estimated ~16,000 premature mortalities in 2018 (projected emissions inventory), and Fann et al. (6) estimated 17,000 premature

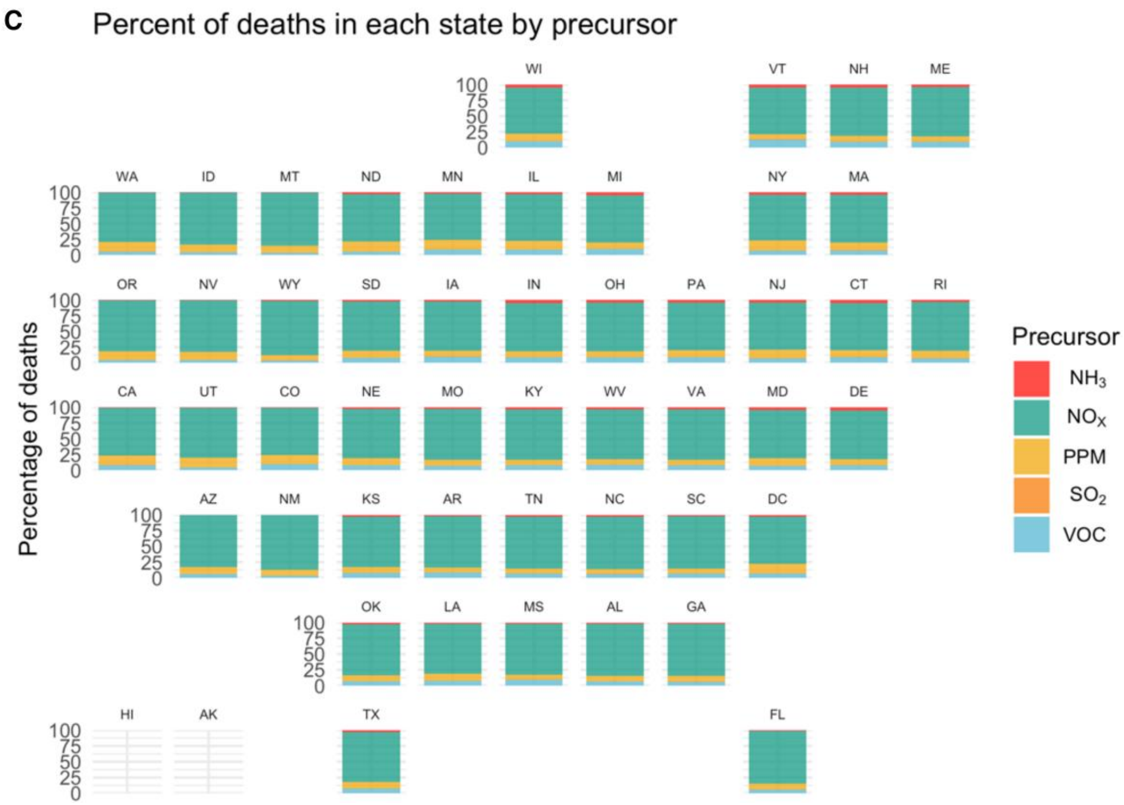

Fig. 3. Continued

mortalities in 2016 (projected emissions inventory). Thakrar et al. (5) estimated 8,200–9,700 premature mortalities (estimates ranged from three reduced complexity models) from PAS vehicle use and 3,200–7,700 from truck use. We estimate 11,900 from PAS and 6,670 from FRT. Each of these studies listed has utilized different reduced complexity models or chemical transport models as well as varying CRFs used for the health impact assessments. Additionally, source classification code (SCC) groupings for PAS and truck use in Thakrar et al. (5) vary from our groupings of PAS and FRT.

We can compare our estimates of COVID-19-related road transportation activity/emission decrease with emissions estimates derived from a fuel-based inventory (17). Figures S4 and S5 show the ratio of state-level VMT to prepandemic levels for each month for PAS and FRT, respectively. We observe similar trends for gasoline sales and urban/rural traffic estimates as those in Harkins et al. (17), with most states experiencing the largest decreases in PAS VMT in April and mostly returning to prepandemic levels by the summer. It is important to note though that not all states experience a return to full prepandemic levels by summer, which becomes important when evaluating the annual impacts. FRT VMT does not have as pronounced of a decrease in April similar to what was observed for diesel sales (17). We estimate states experience a 29–62% decrease in PAS VMT and a 2–35% in FRT VMT in April 2020 compared with prepandemic levels. Harkins et al. (17) estimated a 25–51% decrease in gasoline sales in April 2020 and a 4–17% decrease in diesel sales. However, when using the fuel sales estimates to derive mobile source emissions for the month of April, Harkins et al. (17) estimated that state-level reductions to NO_X emissions vary between 6 and 39%. Hence, by equating changes in VMT to changes in emissions, we may be overestimating the reductions experienced during the pandemic when compared with fuel-based-derived emissions inventories. Yet, our estimates of US average VMT/emissions reductions in April 2020 of ∼47 and ∼9% for PAS and FRT, respectively, are in line with other studies that utilized mobility-based estimates of US on-road emissions reductions that found reductions of 40% (41), 45% (42), and 50% (22). Additionally, our upper estimates for PAS VMT changes by state (62% decrease during April 2020) compare well with road transportation emission reduction estimates (60% decrease from 2020 March 22 to May 2) for four large Canadian cities (43). Hence, emissions estimates can vary by whether they are mobility based or fuel based, designated by urban vs. rural and by vehicle type.

Two studies estimate the $PM_{2.5}$ concentration decreases due to on-road activity decreases in Southern California. Yang et al. (44) estimated a 17.5% decrease in $PM_{2.5}$ during the strictest lockdown period in April and a 6% decrease from May to June. Jiang et al. (45) estimated a 15% decrease in $PM_{2.5}$ from the end of February to the end of April 2020. We estimate a decrease in on-road-attributable $PM_{2.5}$ impacts of 13% over the year in the state of California, which seems more substantial than the peak 15–18% in April and the much more modest reductions of 6% by July. Yang et al. (44) utilized a machine-learned model to predict concentration reductions in a shorter lockdown period (2020 April 6 to 12) and a later recovery period (2020 May 8 to June 30) due to traffic changes in the Los Angeles Basin, and Jiang et al. (45) performed a chemical transport model assessment for Southern California for a hypothetical lockdown emissions scenario (average on-road emissions reductions of 45% in the region compared with our PAS reductions of 51% and FRT reductions of 2% in April 2020 in California). Our annual estimates take into account the relative lack of recovery in VMT after the greatest decreases in April in California, with the average VMT reduction from May to December 2020 being

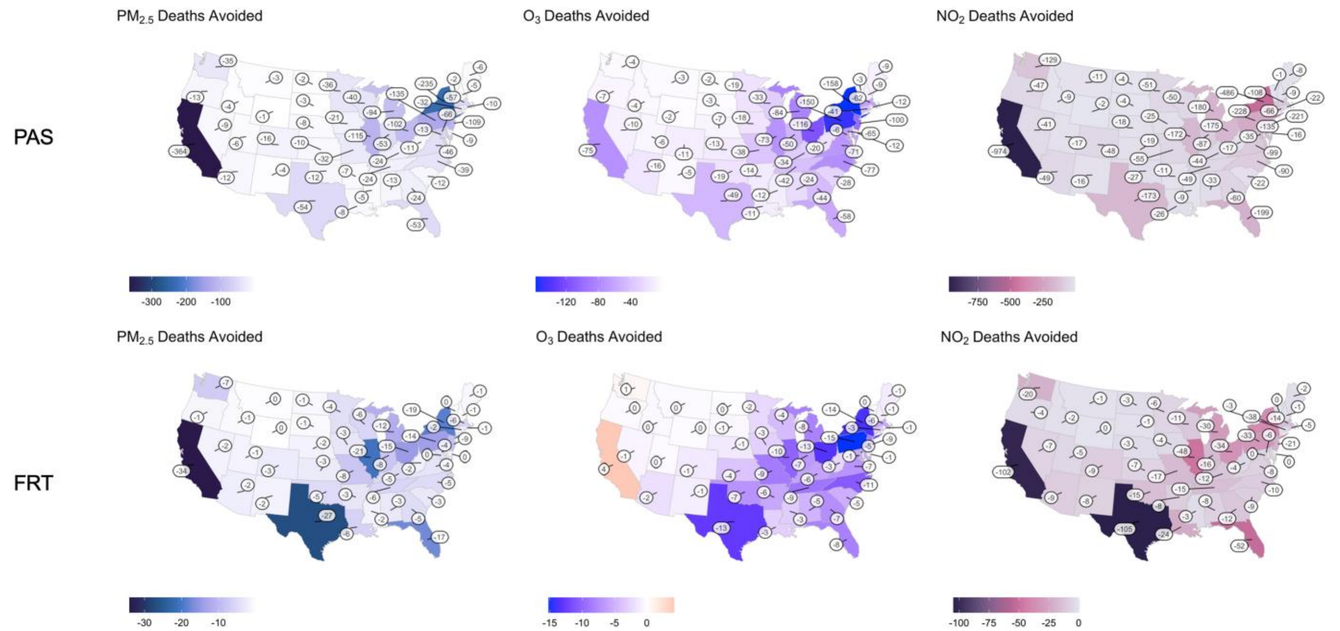

Fig. 4. Premature mortalities were avoided due to VMT reductions from COVID-19.

21%. Additionally, we are not designating urban vs. rural changes across the state resulting in a possible misalignment with the largely urban areas studied by Yang et al. (44) and Jiang et al. (45), which can lead to differing trends (17, 46).

Additional studies have examined the health impacts of COVID-19 lockdowns' impacts on air pollution across the world. In China, Chen et al. (47) estimated ∼8,900 and ∼3,200 premature deaths were avoided from reductions in NO_2 and $PM_{2.5}$, respectively, in January through March 2020; Giani et al. (37) estimated ∼24,000 premature deaths were avoided from reductions in $PM_{2.5}$ in February through March 2020; and Chossière et al. (38) estimated ∼21,000 and ∼54,000 premature deaths were avoided from reductions in NO_2 and $PM_{2.5}$, respectively, in January through July 2020. In Europe, Giani et al. (37) estimated ∼2,200 premature deaths were avoided from reductions in $PM_{2.5}$ in February through March 2020, and Chossière et al. (38) estimated ∼6,600 and ∼6,100 premature deaths were avoided from reductions in NO_2 and $PM_{2.5}$, respectively, in January through July 2020. Globally, Liu et al. (39) estimated between 99,000 and 147,000 premature mortalities were avoided, and Chossière et al. (38) estimated 95,000 were avoided due to lockdowns from January to July. While we find 9,300 deaths were avoided in 2020 due to the reductions in on-road activity across the continental United States, it is difficult to directly compare our results with these studies. These studies relied on observation data (monitor and remote-sensing datasets) to quantify ambient air quality concentrations and lockdown stringency metrics to determine the effects of lockdown restrictions on regional/global levels of air pollutants for short-term impacts. And unless confounding variables, like seasonal variation and interannual trends, are accounted for, the relation of pollution reductions to COVID-19 lockdowns could be mischaracterized (38). This study aims to isolate the impacts of transportation through lockdown restrictions by using annual reductions in on-road activity in each US state in 2020 to quantify the long-term air quality–related health impacts with all else being held equal.

There are some important caveats to this study. We estimate "prepandemic" on-road-attributable air pollution levels from 2016 emissions and meteorology data as that was the most recent NEI available at the time. We utilize relative VMT changes to "pre-pandemic" levels to scale our air pollution sensitivities assuming VMT changes to be equivalent to emissions changes. This differs from some studies that utilize mobility or fuel-based data combined with emission factors to then derive updated mobile source emissions for multiple emissions precursors, often only for a single month or shorter to represent the impacts from lockdowns. The benefit of our modeling choice allows for our precursor-specific sensitivities to be used for other mobility-derived or fuel-based-derived state-specific annual inventories, rather than creating entirely new emissions inventories and having to run the model again. Since the largest VMT reductions occurred during the March to June period, a chemical environment might not be well represented by the January or July setup in Community Multiscale Air Quality (CMAQ)-Decoupled Direct Method (DDM) simulations. However, we modeled two different representative months to capture seasonality and compute annual averages similar to what has been done in at least two other DDM sensitivity-based studies (35, 48). The shorter modeling periods allowed us to model the reductions observed in each state individually, something that would be prohibitively computationally expensive for the entire year. Future work aimed at annual averages can explicitly model the entire year when emissions inventories are available for 2020. We also make use of baseline mortality prevalence datasets that do not include the impacts of COVID-19. As air pollution and COVID-19 both impact respiratory systems, future work should look to incorporate updated background prevalence data in order to determine possible relationships between elevated levels of air pollution and COVID-19 susceptibility (49–53) and their impact on emission reduction strategies. Additionally, we assumed exposure to $PM_{2.5}$, O_3, and NO_2 individually when it is true that people are invariably exposed to multipollutant exposures, which may exhibit varied concentration responses (54–57). This study did not explicitly account for multipollutant exposures, but the CRFs utilized did adjust for co-exposures, allowing for assurance in quantifying independent results. Last, we recognize that the EPA's Integrated Science

Assessment for Oxides of Nitrogen-Health Criteria (from 2016, which is currently being updated) found NO_2 exposures are causal/likely for respiratory effects, and there is still uncertainty regarding the possibility that NO_2 is just a marker of traffic-related pollutants and want to stress caution when interpreting our NO_2 mortality estimates. Canada has quantified mortalities from acute exposure to NO_2 from all sources and found estimates to be on the order of those from $PM_{2.5}$ and O_3 (58). This study adds to the growing literature surrounding certain emission sources having outsized influences with regard to pollutant-specific adverse health outcomes, such as NO_2-related health impacts being larger than those from $PM_{2.5}$ and O_3 from commercial aviation emissions (12) and oil and gas production emissions in the United States (59).

There were ~385,000 deaths in the United States from COVID-19 in 2020 (60). Hence, reductions in air pollution–related premature mortalities from reductions in on-road activity are 2.4% (1.4–3.6%) of total deaths from COVID-19. This compares well with the study by Chossière et al. (38) who found that reductions in air pollution–related deaths per capita represent <2.8% of deaths per capita from COVID-19 in the United States and 6.4% in Europe using ambient pollutant concentrations from January to July in 2020. One of the unintended consequences of the COVID-19 pandemic was the unplanned experiment of reduced anthropogenic emissions impacting air quality. The results of this study highlight the importance of even relatively small reductions in road transportation emissions leading to public health benefits. Additionally, local strategies aimed at reducing VMT from PAS vehicles such as promoting shifts to walking and cycling, and national strategies for reducing emissions from FRT through alternative fuel use can have further public health benefits (61). The EPA's recent proposal for stronger NO_X standards for heavy-duty gasoline and diesel engines aims to reduce NO_X emissions from trucks by as much as by 60% in 2045 (62). While mitigating on-road NO_X emissions' impacts on $PM_{2.5}$-attributable and O_3-attributable health outcomes has been found to be an effective target for improving public health, the results from our study stress the need for stronger NO_X controls.

Materials and methods

In this study, we utilized CMAQ-DDM-based sensitivity coefficients for PAS and FRT vehicles from each state to estimate the air pollution–related adverse health outcomes attributable to $PM_{2.5}$, O_3, and NO_2 exposures across the United States. The sensitivities were used to scale PAS and FRT emissions from each state by VMT changes observed in 2020 (when compared with "prepandemic" levels) to estimate the air pollution changes and the subsequent related adverse health outcomes. Air pollution changes were related to corresponding health outcome changes through BenMAPR—a geospatial air pollution health impact assessment tool inspired by the Environmental Benefits Mapping and Analysis Program (BenMAP). Further details are provided in the following sections.

Air quality modeling

Details regarding our air quality modeling setup and performance (Normalized Mean Bias [NMB] and Normalized Mean Error [NME] were <25 and <50%, respectively) can be found in Arter et al. (12), and details regarding the sensitivity analyses as implemented for this study can be found in Arter et al. (35). Our air quality modeling was performed with on-road vehicle emissions from the US EPA's 2016v1 modeling platform based on the NEI (63, 64). In the NEI, on-road vehicle emissions are generated using hourly meteorological data, emission factors representative of all national fuel economy and greenhouse gas (GHG) emission standards as of October 2015, and county-specific vehicle activity data submitted by each state for 2016 (63). In this study, we generated two emission inventories for each of the 48 contiguous US states representing PAS and FRT vehicles using the Sparse Matrix Operator Kernel Emissions (65) modeling system. Table S1 shows the SCC values used to group the MOtor Vehicle Emission Simulator (66) vehicle types into the PAS and FRT classes.

The DDM sensitivity analysis (67–70) as implemented in CMAQ model version 5.2 (71) with the carbon bond 6 revision 3 mechanism (72) was used to calculate first-order sensitivities of $PM_{2.5}$, O_3, and NO_2 concentrations in each model grid cell to precursor emissions from PAS and FRT in each source state. Our modeling domain encompasses the continental United States with 12 km × 12 km horizontal grid resolution. To decrease computational load, CMAQ-DDM simulations were run for January and July 2016 with a week of the spin-up period to represent the winter and summer seasons, respectively, similar to what has been done in at least two other DDM sensitivity-based studies (35, 48). The results are then averaged to represent the annual contribution of emissions from PAS and FRT in each state to $PM_{2.5}$, O_3 (annual average of the daily 8 h maximum), and NO_2 concentrations. Details regarding model evaluation against observations can be found in Arter et al. (12). To calculate the changes in air pollutant concentrations due to changes in on-road activity as a result of the pandemic, percent changes in the annually averaged VMT are multiplied by the annual average air pollutant sensitivities to precursor emissions from each vehicle class and source state.

VMT changes

The on-road activity analysis was performed with data from the INRIX Analytics big data assessment platform (73). The INRIX Analytics platform analyzes hundreds of millions of anonymized daily trips in the United States and Europe and provides trip trends data including trip volumes, duration, total distance traveled, and average trip distance. INRIX combines data from various sources (e.g. historical traffic data, fleet data, road sensors, mobile data, incident data, consumer vehicle GPS data) to create vehicle trip reports by vehicle type. The fundamental source data included >100 million trips per day from multiple sources, all GPS based. The data included device/trip ID, location, heading, and speed. Each data provider specified the type of fleet or vehicles in their report. Since INRIX Trip Trends covers the entire network (when compared with traditional volume counters), it is supposed to capture all trips (100%) in the United States broken down by three vehicle classes: PAS, fleet, and long-haul trucks (using the data provider classification to create these three vehicle classes). In our study, we used VMT, a common measure of roadway use to adjust the on-road mobile emissions for CMAQ-DDM simulations. We used a daily time series of VMT reduction ratios from INRIX during 2020. The VMT reduction ratio is defined as a ratio of VMT for a given day and VMT for the same day of the week prior to the pre-lockdown control period. The control period is defined as nonholiday days from 2020 January 20 to February 28, prior to the COVID-19 lockdown period. The VMT ratios are broken down by vehicle type: light-duty trucks (PAS vehicles) from 0 to 14,000 lb, and heavy-duty trucks (long-haul trucks)—>26,000 lb. Since traffic data tend to be highly seasonal (typically low in fall and winter, rise in spring, continue to rise through the summer, and decline in fall), we used seasonally adjusted VMT ratios from INRIX Analytics (74), so the data from 1 month can be compared with data from any other month, and the entire series can be ranked to find highs and lows. Figures S4 and S5 show the ratios of monthly PAS and FRT VMT in 2020 when compared with "prepandemic" levels in each state. Figure S1 shows the annually averaged percent change in VMT in each state.

Health impact analyses

Health impact assessments were carried out using BenMAPR. BenMAPR is a geospatial air pollution health impact assessment platform written in the statistical computing language R, which quantifies the air quality–related adverse health outcomes to exposed populations. BenMAPR (code available on GitHub at: https://github.com/jjbuonocore/BenMAPR) has been used in other health impact analyses (12, 35, 59) and relies on similar calculations and datasets used in BenMAP (75). Mortality CRFs were chosen that best represent our study domain, with a focus on CRFs from studies that were either meta-analyses of many studies or studies with large multiyear, multilocation cohorts. For quantifying $PM_{2.5}$-attributable premature mortalities, we make use of a concentration response function (CRF) from a recently published meta-analysis (76) that found a 1.29% (95% CI 1.09–1.5) increase in all-cause mortality per 10 $\mu g/m^3$ increase in $PM_{2.5}$. For O_3-attributable premature mortalities, we use a CRF associating all-cause mortality to long-term O_3 exposure with a hazard ratio of 1.02 (95% CI 1.01–1.04) per 10 ppb increase in O_3 (77). For NO_2-attributable premature mortalities, we use a CRF from a meta-analysis that found a pooled effect on mortality to be 1.04 (95% CI 1.02–1.06) with an increase in 10 $\mu g/m^3$ in NO_2 (78). A value of statistical life approach was used to monetize the value of the change in mortalities by multiplying the number of $PM_{2.5}$-attributable, O_3-attributable, and NO_2-attributable mortalities by a 2016 USD ($) income-adjusted value of $10.3 million as recommended by the EPA (79). Details regarding the CRFs and underlying background prevalence/incidence data can be found in Table S2 and in Arter et al. (12).

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Supplementary Material

Supplementary material is available at *PNAS Nexus* online.

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Author Contributions

C.A.A.: methodology, investigation, data curation, software, formal analysis, and writing—original draft. J.J.B.: software, data curation, and writing—review and editing. V.I.: methodology, investigation, data curation, and writing—review and editing. G.P.: data curation, methodology, and investigation. S.A.: conceptualization, methodology, validation, supervision, project administration, resources, funding acquisition, and writing—review and editing.

Data Availability

The models used in this study are publicly available on Github at: https://github.com/USEPA/CMAQ/tree/5.2 and https://github.com/jjbuonocore/BenMAPR. The emissions inputs used are available at: https://gaftp.epa.gov/Air/emismod/2016/v1/.

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