


Article

Expected Health Effects of Reduced Air Pollution from COVID-19 Social Distancing

Steve Cicala ^{1,†} , Stephen P. Holland ^{2,†}, Erin T. Mansur ^{3,†}, Nicholas Z. Muller ^{4,†} and Andrew J. Yates ^{5,*,†}

¹ Department of Economics, Tufts University and NBER, 317 Braker Hall, 8 Upper Campus Rd., Medford, MA 02155, USA; scicala@gmail.com

² Department of Economics, University of North Carolina at Greensboro and NBER, Bryan 462, Greensboro, NC 27402, USA; sphollan@uncg.edu

³ Tuck School of Business at Dartmouth and NBER, 100 Tuck Hall, Dartmouth College, Hanover, NH 03755, USA; erin.mansur@dartmouth.edu

⁴ Department of Engineering and Public Policy, Tepper School of Business, Carnegie Mellon University and NBER, Posner 254C, 5000 Forbes Avenue, Pittsburgh, PA 15213, USA; nzm@andrew.cmu.edu

⁵ Department of Economics and Environment, Ecology, and Energy Program, The University of North Carolina at Chapel Hill, Chapel Hill, NC 27599, USA

* Correspondence: ajyates@email.unc.edu

† These authors contributed equally to this work.

Abstract: The COVID-19 pandemic resulted in stay-at-home policies and other social distancing behaviors in the United States in spring of 2020. This paper examines the impact that these actions had on emissions and expected health effects through reduced personal vehicle travel and electricity consumption. Using daily cell phone mobility data for each U.S. county, we find that vehicle travel dropped about 40% by mid-April across the nation. States that imposed stay-at-home policies before March 28 decreased travel slightly more than other states, but travel in all states decreased significantly. Using data on hourly electricity consumption by electricity region (e.g., balancing authority), we find that electricity consumption fell about 6% on average by mid-April with substantial heterogeneity. Given these decreases in travel and electricity use, we estimate the county-level expected improvements in air quality, and, therefore, expected declines in mortality. Overall, we estimate that, for a month of social distancing, the expected premature deaths due to air pollution from personal vehicle travel and electricity consumption declined by approximately 360 deaths, or about 25% of the baseline 1500 deaths. In addition, we estimate that CO₂ emissions from these sources fell by 46 million metric tons (a reduction of approximately 19%) over the same time frame.

Keywords: air pollution; COVID-19; social distancing; carbon emissions



Citation: Cicala, S.; Holland, S.P.; Mansur, E.T.; Muller, N.Z.; Yates, A.J. Expected Health Effects of Reduced Air Pollution from COVID-19 Social Distancing. *Atmosphere* **2021**, *12*, 951. <https://doi.org/10.3390/atmos12080951>

Academic Editors: Seyed M. Karimi, Bert Little, Mahdi Majbourni and Hamid Pouran

Received: 11 June 2021
Accepted: 20 July 2021
Published: 23 July 2021

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

The novel coronavirus outbreak, along with measures intended to contain the spread of COVID-19, resulted in significant and, in some cases, unprecedented, changes in society. Social distancing and other measures led to a dramatic decline in economic activity [1]. In a fossil fuel-based economy, such as the U.S., a large adverse demand shock is likely to have appreciable repercussions for emissions and ambient pollution levels. Though long-run outcomes are not yet discernible, it is feasible to assess near-term changes in certain measures of environmental quality. Furthermore, because there is an established literature linking exposure to ambient pollution to various health outcomes, it is possible to gauge the effects of such changes on public health [2,3]. The goal of this analysis is to quantify the health effects of these unprecedented changes from two channels: reduced travel and electricity consumption. In recent years, emissions from travel and electricity generation account for between 25% and 50% of national total emissions for several pollutants (see

Table A1 in Appendix A). Hence this quantification is an important input in an economic analysis of social distancing.

Our analysis uses cell phone data, which are reported daily for every U.S. county, to measure changes in mobility, and, by extension, vehicle-miles traveled, over the February to April 2020 period. For electricity, we employ hourly data by electricity region (e.g., balancing authority) to estimate the changes in electricity consumption, and the corresponding emissions, over the same time period controlling for observable factors, such as temperature and a battery of temporal fixed effects. We focus on reductions in emissions ($PM_{2.5}$, SO_2 , NO_x , and VOCs) that contribute to the formation of fine particulate matter ($PM_{2.5}$). We use integrated assessment modeling to connect emissions to changes in ambient $PM_{2.5}$ and the associated reductions in expected adverse health effects from exposure to pollution. Of particular interest are reductions in $PM_{2.5}$ -associated mortality risk, as this health endpoint contributes the largest share of air pollution damages [4].

Our study contributes to the literature that uses integrated assessment modeling to analyze human health effects of pollution emissions from economic activity. Previous studies that use similar methodology include, for example, analysis of emissions from pipeline and rail shipments of petroleum products, the emissions consequences of moving from gasoline vehicles to electric vehicles, and the emissions reductions from increasing solar generation of electricity [5–7]. Our paper also contributes to the general literature on the determinants and consequences of social distancing policy [8–13]. Finally, our paper complements contemporaneous work on the coronavirus' effect on outdoor air pollution in North America [14–16], Europe [17,18], and Asia [19–22], and indoor air pollution [23]. Relative to these other papers, our contribution is two-fold. First, we analyze reductions in emissions by source (either travel or electricity generation) and second we map these reductions in emissions to spatially disaggregated human health outcomes.

Section 2 describes the data sources and methods for our estimation of the reduction in deaths from reduced travel and reduced electricity consumption. Section 3 describes the results, Section 4 provides a discussion of the results with some caveats.

2. Materials and Methods

Calculating the expected health effects of the reductions in personal vehicle travel and electricity consumption from social distancing has three components: first, estimating the reduction in travel or electricity consumption; second, calculating the resulting reduction in emissions; and third, calculating the health effects of the reduction in emissions. To estimate the reduction in travel or electricity consumption, we use estimates of counterfactual travel or electricity usage based on historical data with controls for relevant confounding variables, e.g., weather. Next, estimates of emission reductions are based on emissions rates per unit of travel or on observed emissions from power plants. Finally, the health effects of the reductions in emissions are calculated from the AP3 integrated assessment model [5,24,25]. AP3 maps emissions of different primary pollutants from different sources (counties or point sources) into ambient concentrations of secondary pollutants at receptor counties and uses dose-response relationships and county-specific demographics to calculate expected deaths from the emissions. Below, we describe the procedure for estimating health effects from reductions in travel and electricity usage in turn and then give details of the AP3 model.

2.1. Personal Vehicle Travel

To estimate the health effects of reduced vehicle travel, we combine estimates of the reduction in travel with emission rates per mile and estimates of the marginal health effects (marginal damage) per unit of emissions. First we determine the reduction in travel. Comprehensive data on vehicle miles traveled (VMT) is reported by a variety of state agencies and collected at the national level. However, our analysis requires high frequency data to estimate the effect of social distancing that has only been in effect for a short time. For high-frequency travel data, we turn to Unacast [26]. Unacast, which specializes in

mobility data analysis, created a pro bono COVID-19 toolkit to help researchers and to raise public awareness of social distancing. Unacast analyzed cell phone mobility data to calculate a percentage reduction in distance traveled for each county. To date, Unacast has not provided information on the time frame over which they estimated counterfactual travel reductions and which control variables they included. In Appendix A, we analyze data from Streetlight, who use an alternative methodology to infer VMT from cell phone mobility data. The results are similar for the two sources. We also present evidence from gasoline sales. An important confound might be the concurrent, dramatic fall in gasoline prices. Because the decreasing gasoline price would tend to increase gasoline consumption, our calculations may understate the true effect. We combine these percentage reductions with county-level estimates of light duty vehicle VMT from the US EPA MOVES model to determine the reduction in VMT in each county. Light duty vehicles include cars, minivans, sport utility vehicles (SUVs), and some pick-up trucks. By applying the Unacast percentage reduction to all light duty vehicles, we are assuming that reductions in travel are proportional across the vehicle classes.

Second, we use fleet average emissions rates of SO_2 , $\text{PM}_{2.5}$, NO_x , and volatile organic compounds (VOCs) to map the reduction in travel into the reduction in emissions. Emission rates for $\text{PM}_{2.5}$, NO_x , and VOC are based on national average fleet characteristics and fuel properties in 2018 and are reported in Tables 4–43 in [27]. The emissions rate for SO_2 assumes 22.3 fleet average mpg [28] and 10 ppm sulfur in gasoline, which reflects the latest gasoline sulfur content regulations. Carbon emissions per mile can be calculated from this mpg and the carbon content of gasoline.

Third, we use data from the AP3 model that delineates marginal damages per unit of emissions in each county to map the reduction in emissions to reduction in marginal damages.

2.2. Electricity Use

To estimate the health effects of reduced electricity usage, we combine estimates of the reduction in electricity use with estimates of the marginal health effects (marginal damage) per unit of power produced.

The reduction in electricity usage is estimated from data from individual independent system operators (ISOs) and the Energy Information Administration (EIA) on hourly electricity consumption, referred to as ‘system load’. System load is the aggregate of all power taken from the grid, including residential, commercial, and residential customers, as well as line losses. ISOs and the EIA vary in the geographic specificity of their reporting, ranging from zones covering local municipal utilities to the entire Tennessee Valley Authority. We refer to each reporting unit as a power control area (PCA) to simplify the distinction between types of load zones and balancing authorities. In total there are 105 PCAs in our data.

We match hourly load data to local temperature readings from the National Weather Service’s Automated Surface Observing Systems (ASOS), a network of automated weather stations that are typically located at airports. These stations are matched to counties, and multiple stations’ data are aggregated up to the PCA using population weights. To account for behind-the-meter generation, we also include hourly reports of solar generation for PCAs in California and New England.

To develop an estimate of reduced electricity consumption, we pool hourly readings of load and temperature from 2017-present. For each PCA, we regress the natural logarithm of hourly load on a set of day of week, hour of day, and week of year dummies. These control for the regular fluctuations in consumption that follow the clock and calendar. Hourly temperature data allow us to control for heating and cooling with the inclusion of a measure of prevailing temperature relative to 18 degrees Celsius (see [29] for more details on the data assembly and estimation). Our estimate of the reduction in electricity consumption in a PCA is the remaining unexplained variation in electricity consumption, which is captured by a set of dummies for each date of interest.

We estimate the health effects of these reductions in electricity consumption using a two-step procedure similar to that in Holland et al. [30] for estimating marginal damages. The first step is to determine hourly expected deaths from pollution from power plants. The second step is to determine the change in expected deaths from a change in electricity consumption.

In the first step, we use data reported from EPA's Continuous Emissions Monitoring System (CEMS) to measure hourly emissions of SO₂, NO_x, and PM_{2.5} at each of the approximately 1500 fossil fuel fired power plants in the contiguous U.S. SO₂ and NO_x are directly reported, and we impute hourly PM_{2.5} emissions based on average emissions rates and observed hourly generation. CEMS also reports carbon emissions. We use a similar procedure to estimate marginal carbon emissions from a change in electricity usage. Holland et al. [30] report a dramatic decline in emissions in recent years, so we use emissions from 2017, which is the most recent year in their dataset. Based on the location of each power plant, we use the AP3 model to map emissions of each pollutant into expected deaths. We then aggregate across pollutants and across power plants within an interconnection to calculate the hourly expected deaths from the pollution.

In the second step, we regress hourly expected deaths on hourly electricity load in each interconnection: East, West, and Texas. We aggregate deaths and load to the interconnection because electricity generally flows throughout an interconnection and PCA loads are highly correlated. See [30]. More specifically, let D_t be the expected deaths in the interconnection due to emissions of all pollutants from all power plants in an interconnection in hour t . Our estimating equation is

$$D_t = \beta Load_t + \alpha_{mh} + \epsilon_t, \quad (1)$$

where $Load_t$ is electricity usage in the interconnection in hour t and α_{mh} are month of sample times hour fixed effects (1 year * 12 months * 24 hours fixed effects). The coefficient β is the change in expected deaths from a change in electricity consumption in the interconnection.

2.3. The AP3 Model

The AP3 model accounts for pollution dispersal, ambient pollution levels, and population density and ages, and hence emissions of different pollutants have different effects in different locations. AP3 maps emissions of local air pollutants to concentrations, population exposure, and premature deaths in each of the 3109 counties in the contiguous U.S. [5]. AP3 is an updated version of the AP2 model [4,31].

The first step in the model matches emissions reported in the 2014 National Emissions Inventory (NEI) to the location of release, by source type. The model differentiates between ground level area source emissions (vehicles, residences, and small businesses) and point source emissions (power plants and factories). In the second step, AP3 uses an air quality model to link annual total emissions to annual average concentrations of both primary and secondary ambient PM_{2.5}. At its core, the air quality modeling approach used in AP3 is Gaussian (see appendix to [32]). Further, AP3 employs multi-year average weather data to model dispersion. AP3 models primary PM_{2.5}, (dispersion), and secondary organics resulting from emissions of VOC are modeled using conversion rate constants. For the other pollutants (NO_x, SO₂, and NH₃), AP3 analyzes their contribution to ambient secondary PM_{2.5} by modeling the interactions among nitrate, sulfate, and ammonium in each receptor county. The approach to modeling ammonium sulfate formation follows the same method as in AP2. However, AP3 employs a regression-based method that estimates ammonium nitrate formation from NO_x emissions. As with AP2, NO_x emissions are linked to ambient gaseous nitrate using conversion rate constants and dispersion. Next, in each receptor county, AP3 fits a polynomial to the process that links gaseous nitrate, and free ammonia, to the formation of particulate ammonium nitrate. The polynomial controls for temperature and humidity. The polynomial was fit to daily predictions from the CAMx chemical transport model. References [24,25] report the quality of the PM_{2.5} predictions in AP3. The third step uses population and mortality rate data (from the U.S. Census and the Centers for

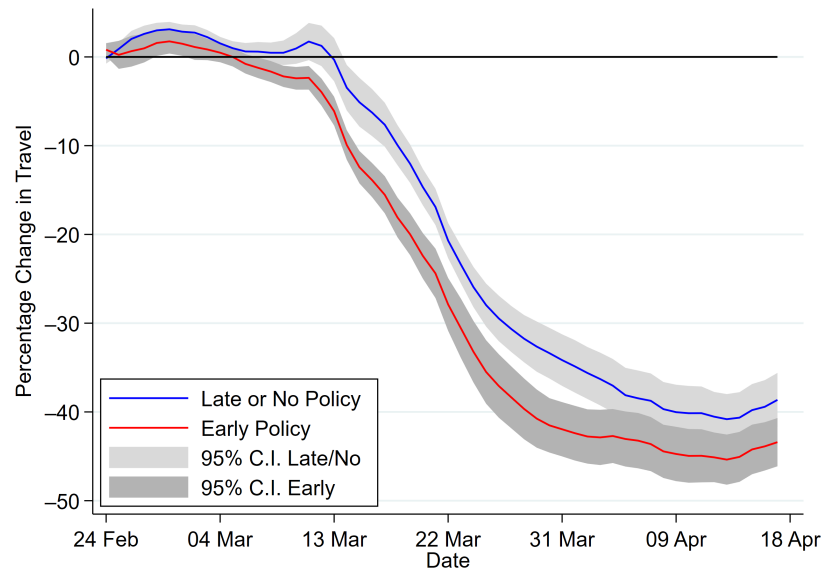
Disease Control and Prevention) by age-group and county to estimate exposures in 2014. The fourth and final step employs peer-reviewed concentration-response functions, linking exposure to changes in adult mortality rates to estimate the mortality risk consequences of emissions [2,3]. The coefficients reported in [2] relate changes in annual average PM_{2.5} to annual, adult, all-cause mortality risk. As a result the damages should not be interpreted as due to transient reduction in pollution and the associated acute health effects.

With all these steps in place, the model determines the premature deaths per unit of pollution (marginal damages). To do this, AP3 first determines baseline deaths due to baseline emissions (as reported by the USEPA in the 2014 NEI). Then one (U.S. short) ton of emissions of some pollutant, for example SO₂, is added to baseline emissions at a given source of pollution (county or power plant) and AP3 calculates the resulting change in concentrations, exposure, and physical health effects. These changes occur in many locations that receive pollution from the source, so that the marginal damages are the sum over all these locations. A similar procedure is repeated for all sources and pollutants covered by AP3.

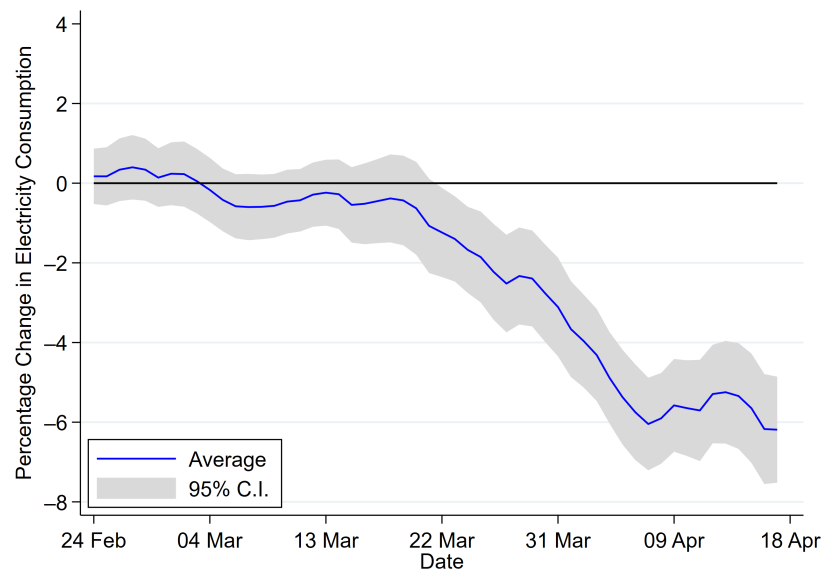
The AP3 model accepts changes to annual emissions as inputs and produces changes to annual average, county-level concentrations as outputs. Whether the emission changes manifest within a particular month, or as an evenly distributed change throughout the year does not affect the relationship between emissions and annual average concentrations in the AP3 model. The ability of the AP3 model to reliably reproduce observed annual average concentrations at USEPA's monitoring across the contiguous United States has been documented in prior work [24,31]. The approach to modeling the relationship between emissions, annual average concentrations, and subsequent health impact calculations used in the present study has been used in numerous studies [33], Chapter 5, page 10).

3. Results

The reduction in light-duty vehicle travel is summarized in Panel (a) in Figure 1 which shows the seven-day moving average of the VMT-weighted average reduction across counties for two groups: counties in states that had an early stay-at-home policy in place by March 28 and counties in states that did not (some of which imposed a stay-at-home policy at a later date) The robust standard errors for the confidence intervals are clustered at the state level and account for serial correlation and correlations across counties within a state. Before early March there is no reduction in VMT, but by the end of March, VMT fell by approximately 40%. States with early stay-at-home policies reduced travel more than others, however, there is a substantial reduction in travel in all the states. An F-test of an equal reduction during the last week of our data is rejected at the 5% level. Data from individual states are shown in Figure A1 in Appendix A Since early April, the VMT reduction seems to have stabilized at around a 40% average reduction. We use the last week of data (from 11 April to 17 April) to calculate the reduction in light duty VMT for each county relative to the baseline. Recent research by Tanzer-Gruener et al. [16] conducted using ground-level field measurements of ambient local air pollution corroborates the connection between urban air quality and changes in transportation emissions. They observe reductions in constituents of nitrogen oxides (specifically nitrogen dioxide, NO₂) of about 50% that match well with the Unacast data in the Pittsburgh, Pennsylvania metropolitan area, which shows that personal travel was reduced by 46% during the same time period.



(a) Personal vehicle travel



(b) Electricity consumption

Figure 1. Effect of social distancing on travel and electricity consumption. Notes: Seven day moving averages. Data from [26,29]. Early-policy states put a stay-at-home policy in place by 28 March 2020. Shaded area indicates 95% confidence interval.

The fleet average emissions rates (in grams per mile) are shown in Table 1. Additionally shown are the VMT-weighted mean deaths per mile across all counties in the contiguous U.S. The table shows that NO_x emissions are by far the most harmful pollutant from the current vehicle fleet resulting in almost two expected deaths per billion miles traveled. Conversely, the very low SO₂ emission rates yield fewer deaths, per VMT, than NO_x. Combined, these four pollutants account for over three expected deaths per billion miles traveled. Using the fleet average mpg and the carbon content of gasoline, we can also calculate the average CO₂ emissions per mile.

Table 1. U.S. light duty vehicle fleet emissions rates and expected death rates.

Pollutant	Emissions (g/Mile)	Deaths Per Billion Miles
SO ₂	0.003	0.031
PM _{2.5}	0.013	0.469
NO _x	0.384	1.944
VOC	0.386	0.632

Notes: Deaths are VMT weighted averages across all counties in the contiguous U.S.

To calculate the reduction in expected deaths through reduced travel in a county because of social distancing, we multiply the county-level reduction in miles traveled (summarized in Figure 1 by the county-specific estimates of expected deaths per billion miles (summarized in Table 1. The reduction in expected deaths is mapped in Figure A4 in Appendix A. The reductions in deaths are the greatest in California's urban areas.

The estimated reductions in electricity consumption are shown in Panel b of Figure 1. The figure shows the seven-day moving average of the load-weighted average coefficients across the PCAs. The robust standard errors for the confidence intervals are clustered at the PCA to account for serial correlation. The results show that there are not reductions in electricity usage before early March but by mid-April reductions in electricity usage average about 6%. Because PCAs can cross state boundaries, we do not break out the reduction by state stay-at-home policy.

Table 2 shows the coefficients and standard errors from estimating Equation (1). Results are reported for each pollutant individually, as well as in total. The East is the dirtiest interconnection with three expected deaths per TWh of electricity consumption. The bulk of the harm in the East comes from emissions of SO₂. Marginal electricity consumption is least harmful in the West with less than one expected death per TWh of electricity consumption.

Table 2. Marginal expected deaths per TWh of electricity consumption.

Interconnection	Total	SO ₂	NO _x	PM _{2.5}
East	3.106 (0.147)	2.119 (0.134)	0.554 (0.018)	0.433 (0.008)
West	0.849 (0.026)	0.255 (0.015)	0.297 (0.011)	0.297 (0.012)
Texas	1.698 (0.117)	1.225 (0.106)	0.254 (0.011)	0.219 (0.009)

Notes: Newey–West standard errors (48 h lag) in parentheses. Regressions include month of sample by hour fixed effects.

To calculate the reduction in expected deaths through reduced electricity consumption from social distancing, we multiply the estimated reduction in electricity consumption at a PCA (summarized in Figure 1 by the expected deaths per TWh in Table 2 for the appropriate interconnection. The reduction in expected deaths is mapped in Figure A7 in Appendix A. The reductions are the greatest in the Midwest and Southeast, but are much smaller than from reduced travel.

Social distancing due to the COVID-19 outbreak led to reduced personal vehicle travel and electricity consumption which, in turn, lowered emissions of pollution and expected deaths. We measure the reduction in emissions by comparing the electricity consumption and transportation in April 2020 to the February 2020 baseline and use the AP3 model to map changes in emissions to changes in expected deaths per month of reduced emissions. The overall effect of these changes, aggregated to the contiguous U.S., is shown in Table 3. Our baseline estimated that the number of expected deaths per month from air pollution from all light-duty vehicle travel is 666 expected deaths. Our estimated 40% average reduction in travel implies that the expected deaths is reduced by 314 deaths per month

due to reduced travel. This 47% reduction in deaths indicates that travel reductions occurred disproportionately in high damage locations. The table breaks the reduction in deaths into the precursor pollutant to which they can be attributed. Over half of the reduction in deaths are due to reduced NO_x emissions, but reductions in other pollutants, such as VOCs and PM_{2.5}, also contributed substantially. For electricity consumption, our baseline estimated number of expected deaths per month from air pollution from electricity consumption is 859 deaths. This is a higher baseline than for travel, but the 6% reduction in electricity consumption implies that expected deaths are only reduced by 49 deaths (about 15% of the reduction in deaths from travel). The primary reduction in deaths from electricity consumption can be attributed to reduced SO₂ emissions. Combining the results for the reduction in travel and electricity usage gives a reduction of 363 expected deaths.

Table 3. Monthly reduction in deaths from reduced air pollution.

	Travel	Electricity	Total
Baseline Expected Deaths	665.9	859.0	1524.8
Average Percent Reduction	41.0	6.2	n.a.
Reduction in Expected Deaths			
Total	313.8	48.8	362.6
from SO ₂	3.1	32.7	35.8
from NO _x	195.8	8.9	204.8
from PM _{2.5}	48.9	7.2	56.1
from VOC	66.0		66.0

Notes: Average percent reduction in travel is weighted by VMT. Average percent reduction in electricity is weighted by average load in 2019. Deaths are expected deaths per month.

The preceding analysis focuses on the expected health benefits from local pollutants of the reductions in personal vehicle travel and electricity consumption due to social distancing. Additionally, these reductions imply reductions in CO₂ emissions which we can calculate using similar procedures. In particular, for travel we can use the carbon content of gasoline and the fleet mpg together with our estimated reduction in VMT to estimate the reduction in carbon emissions. Applying this methodology, we estimate that CO₂ emissions were reduced by 35.4 million metric tons from a month of social distancing. For electricity consumption, we use the hourly power plant CO₂ emissions from CEMS to estimate the marginal CO₂ emissions from electricity consumption. Applying these estimates to our estimated reduction in electricity consumption in the various regions implies an aggregate reduction in CO₂ emissions from power plants of 10.5 million metric tons from a month of social distancing. Combining the reductions in CO₂ from travel and electricity consumption implies that the month of social distancing reduced CO₂ emissions by 45.9 million metric tons. This is approximately 19% of the 242 million metric tons that are emitted monthly from driving and using electricity.

Social distancing was not evenly distributed across the country as some states and cities implemented stay-at-home policies while others did not. In addition, behavioral changes differed across regions, and mortality risks (as specified by the AP3 model) differ across counties. Table 4 shows the heterogeneity in the reduction in expected deaths and CO₂ emissions due to the reduction in travel for the top MSAs and states. Social distancing in Los Angeles resulted in the largest reduction in expected deaths (77) and carbon emissions (1.1 million metric tons). New York City had a larger percentage reduction in travel but a smaller reduction in expected deaths (26) because of the lower number of baseline deaths per mile traveled. Behavioral changes in other large cities also induced substantial reductions in expected deaths and in CO₂ emissions. At the state level, social distancing in California led to the largest reduction in deaths (115) and in CO₂ emissions (4 million metric tons) from reduced travel.

Table 4. Monthly reduction in deaths from travel by MSA and state.

	Monthly VMT (Billions)	Baseline Expected Deaths	Percent Travel Reduction	Reduction in Expected Deaths	Reduced CO ₂ Emissions
Total	216.46	665.86	41.01	313.81	35.38
Top MSAs					
Los Angeles	5.83	157.37	48.68	76.61	1.13
New York City	4.27	42.72	61.24	26.39	1.04
Chicago	3.80	24.95	48.38	12.28	0.73
San Diego	2.10	17.27	51.59	8.91	0.43
Santa Ana	2.01	16.54	50.92	8.43	0.41
Atlanta	4.17	15.44	44.65	7.41	0.74
Washington DC	3.04	11.19	53.72	6.34	0.65
Philadelphia	1.80	9.91	54.88	5.45	0.39
Newark	1.39	9.19	56.21	5.31	0.31
Oakland (CA)	1.62	10.53	50.30	5.25	0.32
Long Island	1.44	7.71	53.23	4.34	0.31
Minneapolis	2.30	8.33	49.97	4.31	0.46
Edison (NJ)	1.67	7.64	52.90	4.05	0.35
Tampa	1.98	8.38	46.60	4.03	0.37
San Jose	1.18	6.10	57.88	3.56	0.27
Top States					
California	24.19	240.81	42.73	115.00	4.12
New York	9.88	46.32	50.85	27.52	2.00
New Jersey	5.56	32.85	52.76	17.95	1.17
Florida	14.43	34.45	47.27	16.97	2.72
Illinois	7.39	29.90	41.06	14.06	1.21
Pennsylvania	7.21	22.97	42.67	10.80	1.23
Ohio	9.13	25.61	38.76	10.43	1.41
Texas	17.76	25.61	37.48	10.29	2.65
Michigan	7.04	16.12	52.42	8.89	1.47
Georgia	7.81	19.43	38.89	8.69	1.21
Maryland	4.19	13.99	46.86	6.81	0.78
North Carolina	7.83	15.41	36.23	5.85	1.13
Virginia	6.39	12.67	40.48	5.73	1.03
Massachusetts	4.12	9.91	50.78	5.12	0.83
Minnesota	4.12	9.83	44.42	4.87	0.73

Notes: Average travel reduction is weighted by VMT. Reduced CO₂ emissions in millions of metric tons.

Because the PCAs do not map cleanly into states and MSAs, we aggregate them into geographic areas based on independent system operators and NERC regions. The reductions in expected deaths and CO₂ emissions from electricity consumption in these geographic areas are given in Table A4 in Appendix A. About half of the reductions in expected deaths and CO₂ emissions come from electricity consumption reductions in the Southeast and the Midwest (reduction of 13 and 12 deaths and 2.5 and 2.4 million metric tons of CO₂ emissions). Although California had one of the larger percent reductions in electricity consumption (an 8% reduction), this reduction led to smaller declines in expected deaths and CO₂ emissions due to cleaner electricity generation in the West.

4. Discussion

We note important caveats to our findings. The first set of caveats concern the mapping from emissions to expected deaths using the AP3 model. First, AP3 uses concentration-response functions from the epidemiological literature [2] that assume the incremental risk

from exposure to $PM_{2.5}$ is proportional to baseline mortality rates. Because of heightened mortality risk from COVID-19, our calculated reduction in deaths may significantly understate actual reductions in $PM_{2.5}$ exposure risk. See the Appendix for a further discussion of this issue. Second, during the early stages of the pandemic, access to hospitals and health care resources was limited. Thus, treatments for illnesses (other than COVID-19) and the ability for hospitals to admit patients suffering from other maladies were attenuated due to scarce capacity. As a result, rates of morbidities and mortality for health states exacerbated by pollution exposure were likely higher during the pandemic. A final concern related to our approach centers on exposures. The concentration-response function used herein pertains to the context of populations enduring exposure to ambient $PM_{2.5}$ according to their usual mix of indoor and outdoor activity [2]. Clearly, behaviors changed during the pandemic. One might contend that people stayed indoors more than during normal times. Although this may be true with respect to labor market and retail activity, there is survey evidence that people adapted to the lockdowns by finding other opportunities to be outdoors (<https://theharrispoll.com/a-behavioral-shift/>, accessed on 13 October 2020). Another issue with exposures is that AP3 models dispersion and formation of secondary $PM_{2.5}$ based on multi-year averages of weather conditions by county. So our results should be interpreted as an approximation based on these averages. Thus, while it is possible that exposure levels may have shifted, precisely estimating the extent to which this is true is both beyond the scope of the present study and likely to take years of additional follow-up research. We contend that a near-term estimate based on the existing concentration-response function is unlikely to introduce significant bias into the health benefit results and has immediate, policy-relevant value.

Other caveats include the fact that our econometric estimation of counterfactual emissions and Unacast's estimates of counterfactual mobility are uncertain. Additionally, we are interpreting changes in cell phone mobility data as translating directly into changes in VMT from light-duty vehicles, and we do not model intermodal substitution from public transit to personal vehicle use. Finally, we cannot attribute the observed changes in travel and electricity usage to any specific policy or set of policies but only to behavioral changes as observed over this time frame.

Our work provides insight into the benefits and costs of policies related to social distancing [34]. Of course, the primary inputs to a benefit-cost analysis of social distancing would include avoided coronavirus infections, estimated in the trillions of dollars [12], and reduced economic activity. Our work augments these central arguments with one of the potentially many important non-market outcomes, such as health, education, and the environment. Monetization facilitates inclusion of these health benefits directly into a benefit-cost analysis of social distancing. For example, suppose we assume a value of a statistical life (VSL) of \$9 million and a social cost of carbon of \$50 per ton. Multiplying the reduction in expected deaths by the VSL and the reductions in CO_2 emissions by the social cost of carbon and then adding the results reveals that the national environmental benefit of social distancing is \$5.5 billion per month with about 60% of this benefit from reduced deaths. These benefits accrue substantially from social distancing in large metropolitan areas: about \$750 million per month from Los Angeles and about \$320 million per month from New York City.

5. Conclusions

Social distancing, to control the spread of the novel coronavirus, resulted in unprecedented changes in society and in economic activity. Among these are substantial changes in vehicle travel and in electricity usage. This paper quantifies reductions in travel and electricity usage relative to counterfactuals using highly-resolved data. We find that, at the county level, average vehicle travel fell by about 40% whereas electricity usage dropped by about 6% during the months of March and April 2020. We then combine the estimated reductions in travel and electricity usage with air pollution emissions rates and the AP3 model, which links emissions to ambient concentrations and expected deaths. We find

that the reductions in emissions from travel and electricity usage reduced deaths by over 360 deaths per month. The bulk of this reduction is attributed to less personal vehicle travel, and, in particular, reduced NO_x emissions from this travel. Social distancing in California accounted for about a third of the reduction in deaths with Los Angeles alone contributing 20% of the national total. New York accounted for about 10% of the national total. Furthermore, we estimate that social distancing resulted in approximately 46 million metric tons less CO₂ emissions per month. These results complement existing work on the air pollution effects of the pandemic by explicitly relating changes in behavior to reductions in pollution and corresponding reductions in mortality.

Our findings are specific to the unique circumstances of the initial period of the COVID-19 pandemic in the United States. To conduct this analysis, we matched real-time data sources covering mobility and electricity consumption to the EPA's CEMS data on power plant emissions and the AP3 integrated assessment model. With each of these data sources in hand, the methodology we employ can be applied to analyze other economic shocks in other contexts. Without access to these essential data inputs to model location-specific shocks, however, we caution that it would be inappropriate to simply extrapolate our findings to new situations.

Using observed behavioral changes, our paper demonstrates the degree to which reduced reliance on fossil-fuel based transport and power generation yields public health benefits. In the long run these findings are, perhaps, most interesting when interpreted in the context of a post-COVID-19 economy in which remote working and retail delivery are more common. In this state of the world as observed in early April 2020, power demand is only marginally affected, whereas personal travel declines appreciably. The paper shows significant local health benefits from this adjustment. The extent to which consumption habits revert to their pre-COVID-19 levels remains to be seen.

Author Contributions: All authors contributed equally to this work. All authors have read and agreed to the published version of the manuscript.

Funding: Cicala gratefully acknowledges research support from the Political Economics Initiative at the Becker Friedman Institute at the University of Chicago.

Data Availability Statement: The data that support the findings of this study are available upon request from the authors.

Acknowledgments: We thank Robert Burnham, Iván Higuera-Mendieta, and Nicholas Taborsky for research assistance.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

Appendix A

Appendix A.1. Emissions from All Sources

Table A1 shows the tonnage of emissions of relevant criteria pollutants from the two broad source categories covered by this analysis. Electric power generation contributes about 1.1 million tons of NO_x while highway vehicles (inclusive of light duty cars and heavy duty commercial trucks) emit another 3.3 million tons. Together these discharges amount to 43% of the national total emissions. Power generation and vehicle emissions of primary PM_{2.5} comprise just over 20% of total, national emissions. Releases of SO₂ from these two source categories total up to about 1.3 million tons, or about half of the national total. For volatile organic compounds (VOCs), the total from power plants and vehicles is 1.6 million tons. This is 10% of national VOC emissions.

Table A1. Overall air pollution emissions by source, 2018.

Source	NO _x	PM _{2.5}	SO ₂	VOC
Fuel Combustion: Electric Util.	1114	182	1306	38
Fuel Combustion: Industrial	1143	224	534	110
Fuel Combustion Other	541	343	116	372
Chemical & Allied Product Mfg	47	14	123	77
Metals Processing	70	44	105	29
Petroleum & Related Industries	717	29	104	3145
Other Industrial Processes	330	265	167	346
Solvent Utilization	1	4	0	3052
Storage & Transport	6	17	3	675
Waste Disposal & Recycling	110	230	32	233
Highway Vehicles	3300	100	27	1609
Off-Highway	2653	173	69	1622
Miscellaneous	294	3689	150	4669
Total	10,327	5315	2735	15,975

Notes: Units are thousands of U.S. Short Tons. Data from [35].

Appendix A.2. Additional Travel Data

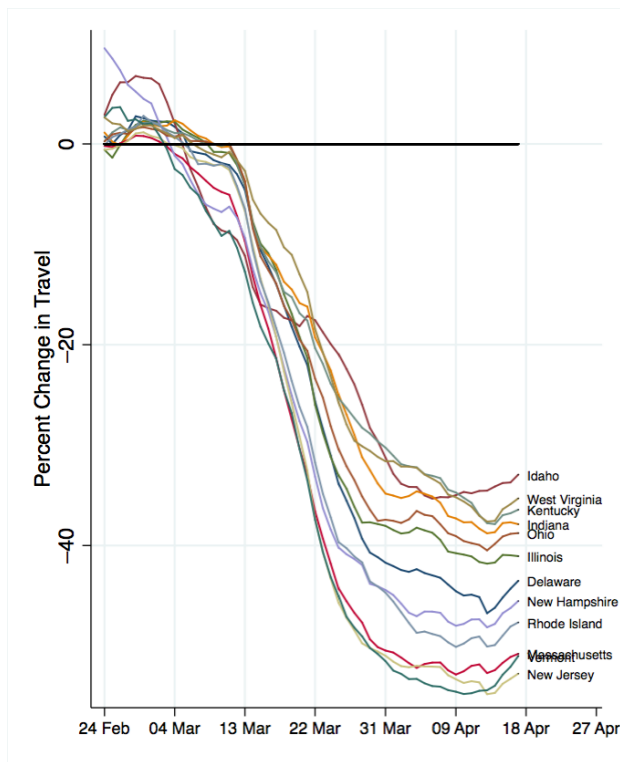
In the main text, we applied the travel reduction percentages from Unacast to the EPA's MOVES estimates of VMT and aggregated the results by states that had early and late policy dates. The results for each individual state are shown in Figure A1.

An alternative source of travel data comes from Streetlight [36]. They use cell phone mobility data to directly estimate reductions in VMT. An analogous figure to Figure 1 made using the Streetlight data is shown in Figure A2. The results from using the Streetlight data to estimate the reduction in deaths from decreased air pollution are given in Table A2. Compared to the results in the main text, the Streetlight data gives a greater decrease in VMT and hence a greater reduction in deaths. However, the decrease in the Streetlight VMT is larger than we would expect from the reduction in gasoline sales documented in Figure A3, and the baseline estimate of total VMT in the Streetlight data is about 40% greater than other estimates. For these reasons, we present the results from the Unacast data in the main text.

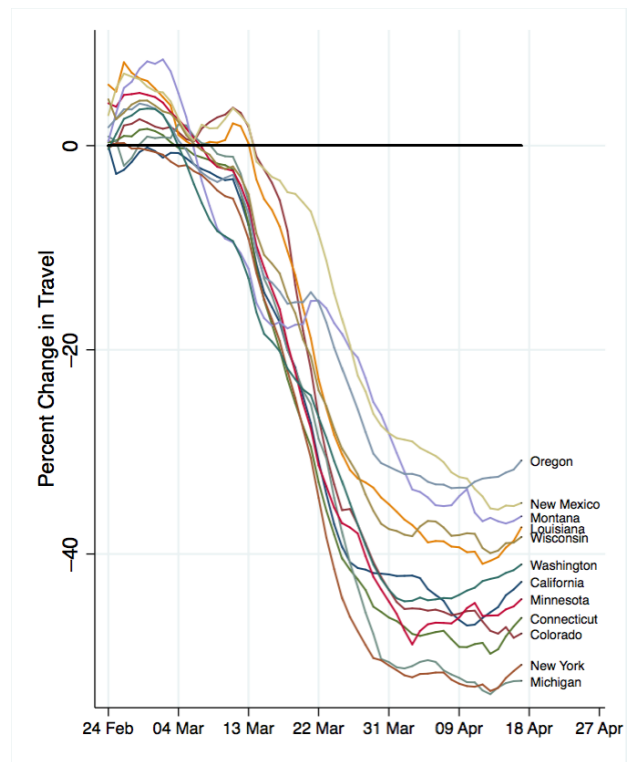
Table A2. Reduction in deaths from reduced air pollution—StreetLight VMT Travel Data.

	Travel	Electricity	Total
Baseline Lives Lost	665.6	859.0	1524.6
Average Percent Reduction	66.9	6.2	n.a.
Reduction in Lives Lost			
Total	492.5	48.8	541.3
from SO ₂	4.9	32.7	37.6
from NO _x	309.9	8.9	318.9
from PM _{2.5}	75.7	7.2	82.9
from VOC	102.0		102.0

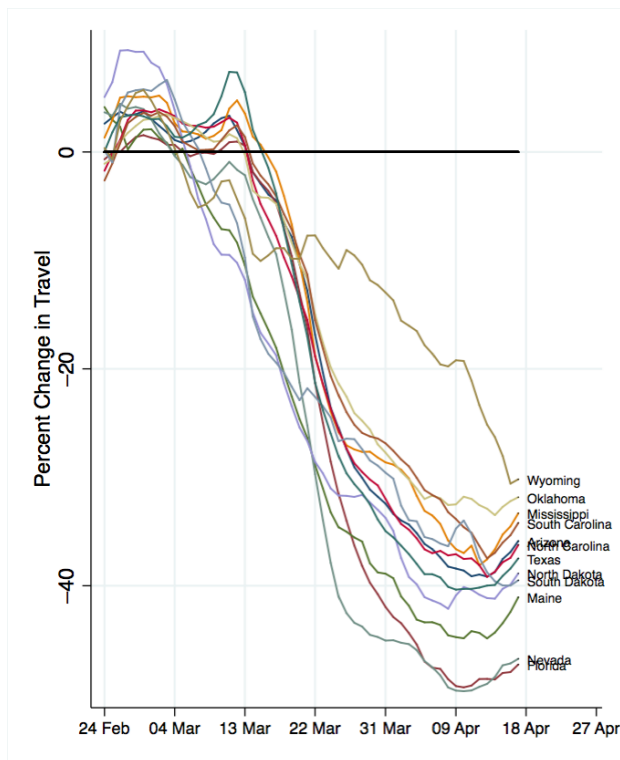
Notes: Average travel reduction is weighted by VMT. Baseline monthly deaths from travel is slightly lower than in Table 3 because there are more counties with missing data.



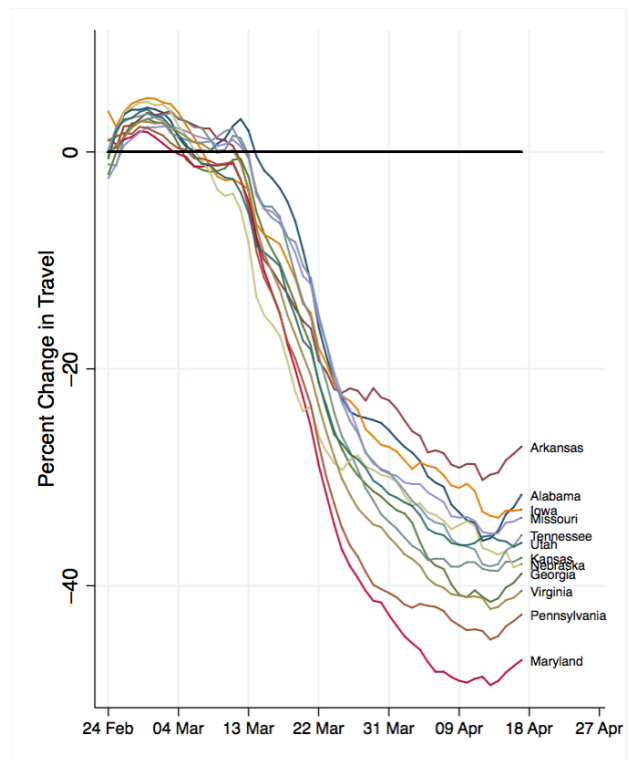
(a) Early Policy States Group A



(b) Early Policy States Group B



(c) Late Policy States Group A



(d) Late Policy States Group B

Figure A1. Personal vehicle travel by state. Notes: Seven day moving averages of VMT weighted county data in each state [26]. Early policy states put a stay-at-home policy in place by 28 March 2020. Groups A and B distinction is arbitrary.

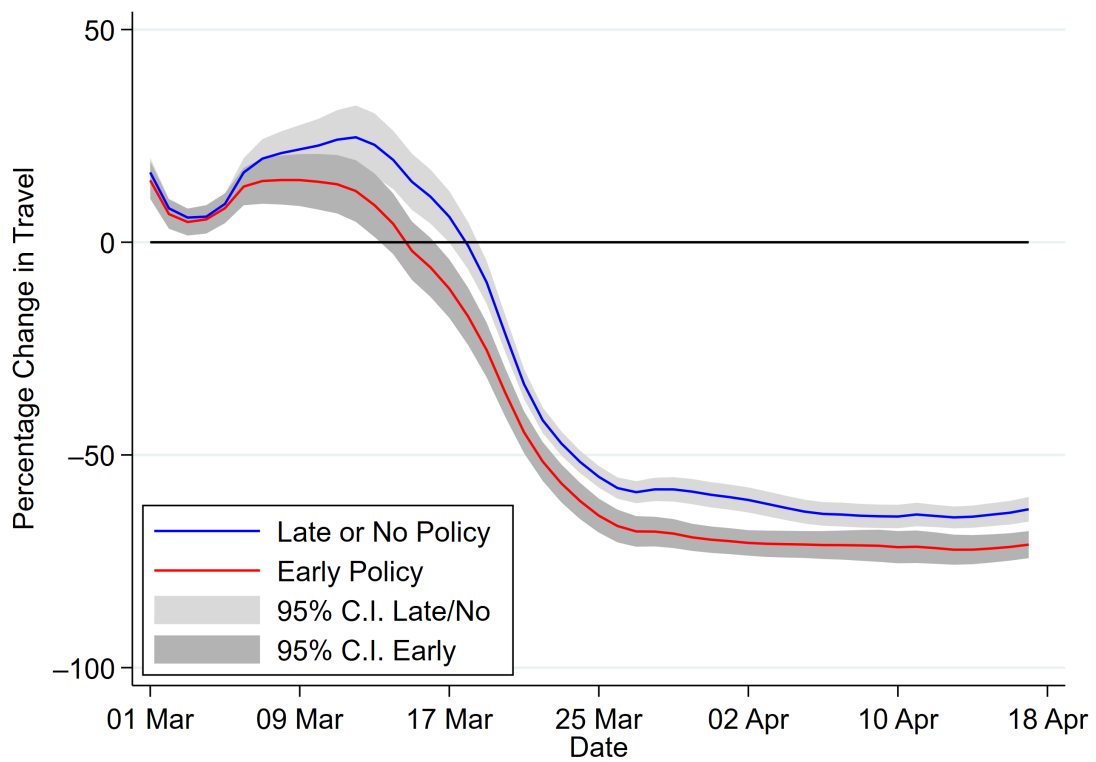


Figure A2. Reduction in StreetLight VMT travel data. Notes: Data from [36]. Baseline is average daily VMT in January 2020. Seven day moving averages. Early-policy states put a stay-at-home policy in place by 28 March 2020. Shaded area shows 95% confidence interval.

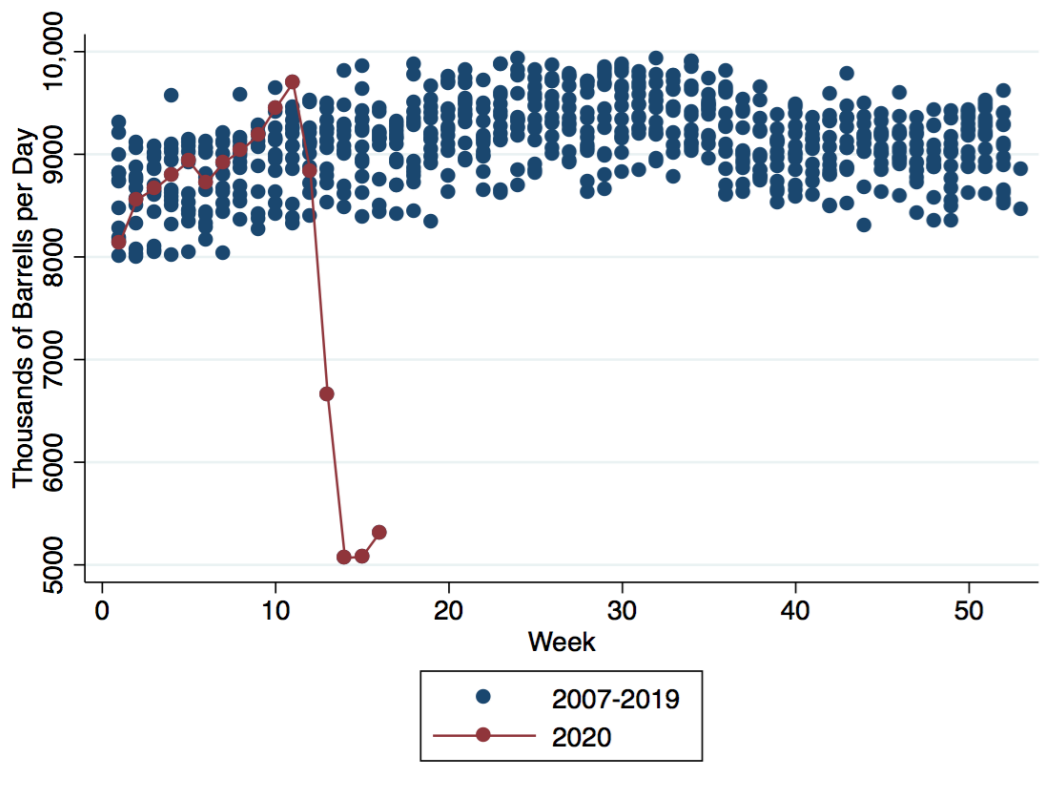


Figure A3. U.S. product supplied of finished motor gasoline. Notes: Data from [37].

Appendix A.3. Weekly Gasoline Sales

An alternative method for inferring changes in air pollution from vehicle travel would be to use changes in gasoline sales. Neither the cell phone data nor gasoline sales data are ideal. The data we use measure the location of all types of mobility each day. Gasoline sales data, which can be obtained from providers such as OPIS, measure gasoline sales at a gasoline station each week. On the one hand, the mobility data more accurately measure where and when activity occurs. However, mobility data do not distinguish between walking, public transport, and driving; they do not inform us on the fuel economy of the vehicle being driven; and the method Unacast uses to measure the baseline is not publicly available. On the other hand, the gasoline sales data more accurately measure the energy use we are studying. However, the gasoline sales data do not provide the location of where the gasoline is being consumed or when it is consumed. There may be a few weeks lag between when gasoline is purchased and when it is used. This lag is a function of driving behavior so it will attenuate the estimate that we are trying to capture at the start of the social distancing responses. Another constraint with using the OPIS data is the cost of acquiring these data. All other data in this paper are free and publicly available.

Figure A3 shows the sales of gasoline, across the entire U.S., by week from 2007–2019 and the beginning of 2020. Before 2020, the sales range between 8000 and 10,000 with an average around 9000 and a small peak in summer consumption (units are thousands of barrels per day). The first 11 weeks of 2020 are within this range, but starting with the 12th week (20 March) there is 40% drop down to about 5000. This decrease is well outside the historical norm, but is consistent with the drop in travel from the Unacast data. Sales remain depressed at this low level for the last three weeks of data (up to 17 April). Further evidence comes from monthly gasoline sales at the state level from EIA [38]. Table A3 shows that there is generally good agreement between the decrease in gasoline sales by state in March and April and the corresponding decrease in travel as measured by the Unacast data.

Table A3. Comparison of travel data with gasoline sales data.

Month-Group	Number Observations	Unacast Travel Percent Reduction	EIA Gas Sales Percent Reduction	Correlation
March-Early	24	20.9	18.0	0.55
March-Late	25	16.7	11.9	0.38
April-Early	24	42.7	38.3	0.82
April-Late	25	38.2	34.4	0.68

Notes: EIA [38] gasoline sales are by state and month. Unacast [26] distance traveled are aggregated to the state and month as well. For example, the March-Early cell contains data for the values of these variables in March for the 24 states that had stay-at-home policies in place by 28 March. Gas sales reduction is 2020 sales as a percent of average 2016–2019 sales by state and month.

Appendix A.4. Supplementary Information about Reductions in Expected Deaths

Figures A4 shows the reduction in deaths from reduced travel at the county level. The spatial distribution of the reduction in deaths depends on reduced travel from COVID-19, observed vehicle miles traveled, population exposure per ton of emissions, and demographics of the exposed population. The reduction in deaths for a given county corresponds to the number deaths that were averted due to reduced driving in the county. This does not mean that all, or even most, of the deaths would have occurred in that county. Due to the dispersion of pollution, many other counties would have received the pollution, and, therefore, received the deaths. Figure A5 shows the reduction in deaths received at the county level. Figure A6 breaks down the reduction in deaths received by pollutant and normalized by population to express the results in mortality rates.

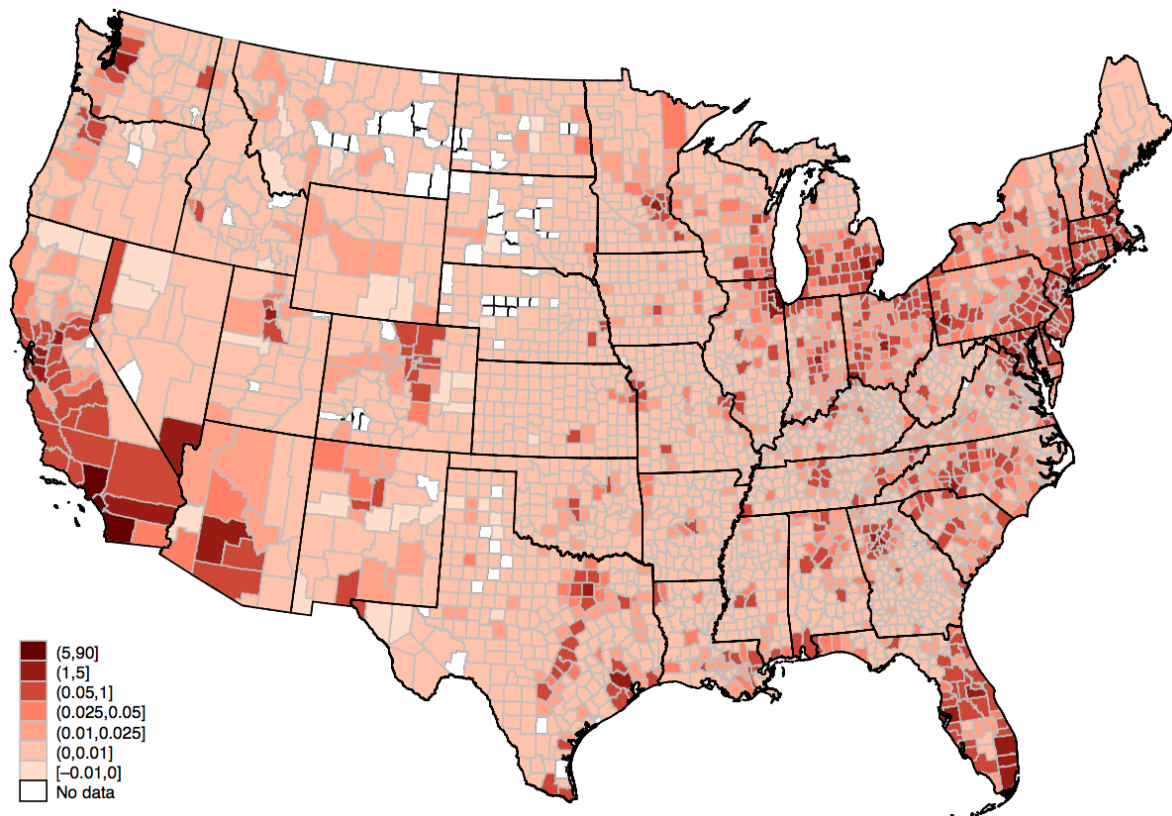


Figure A4. Reduction in deaths: travel. Notes: Figure shows monthly reduction in expected deaths from reduced travel in each county.

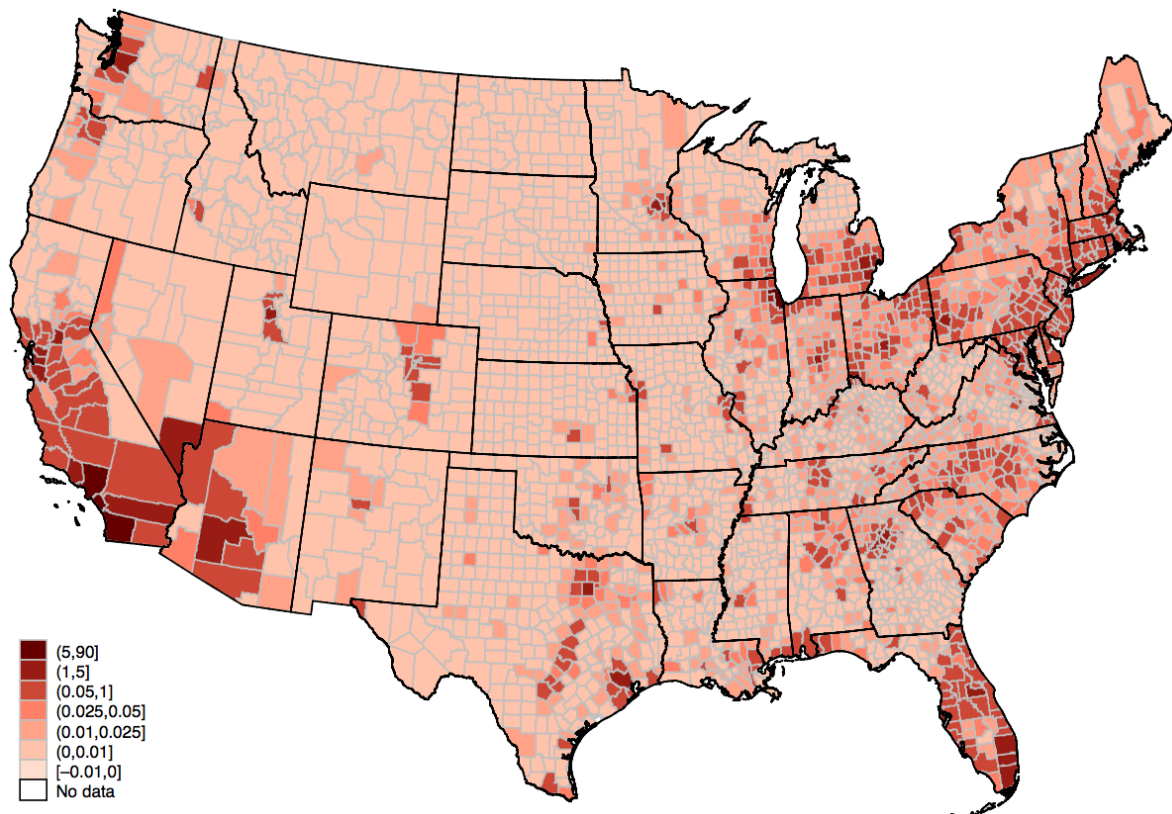


Figure A5. Reduction in deaths received: travel. Notes: Figure shows monthly reduction in expected deaths received in each county.

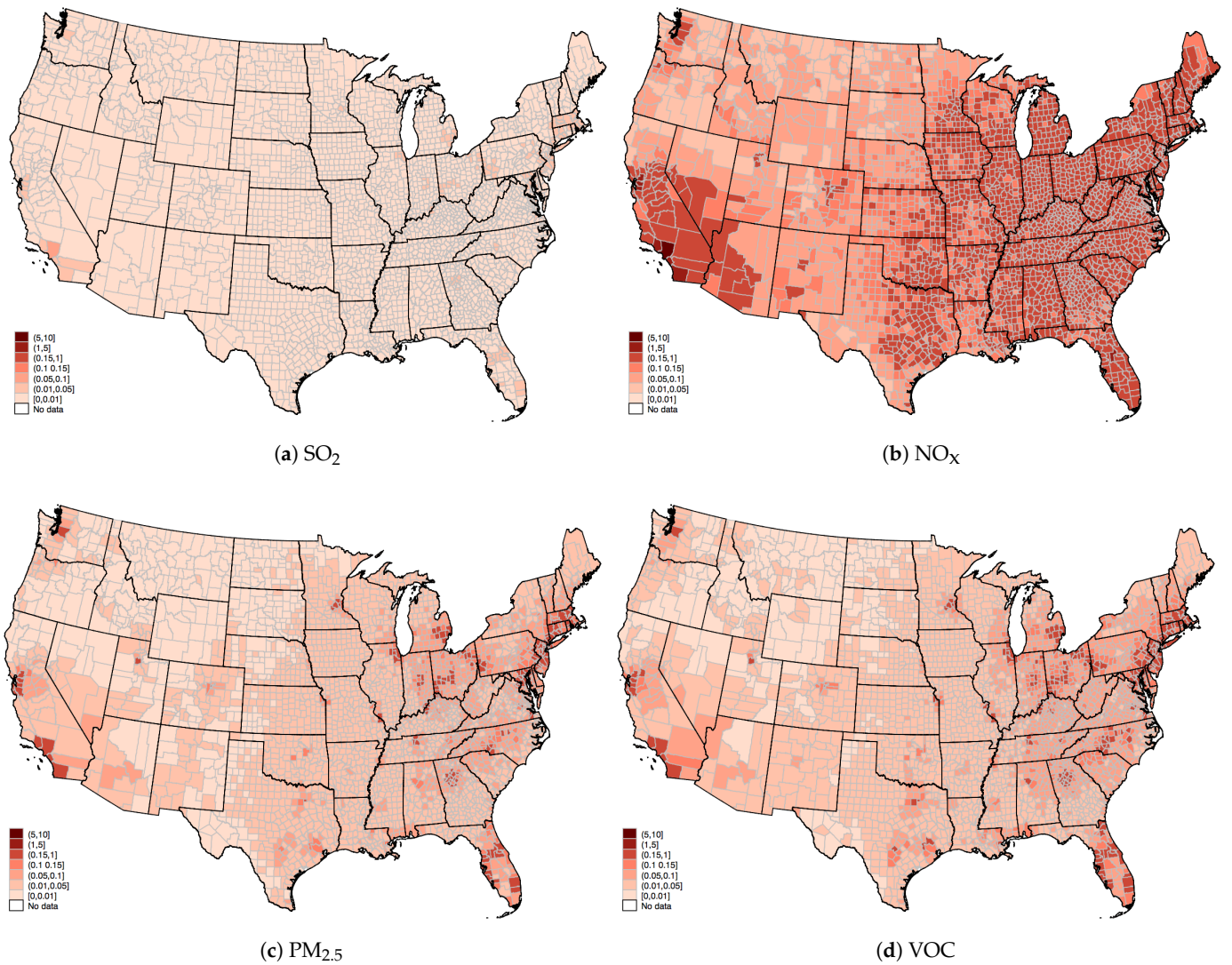


Figure A6. Reduction in mortality rate: travel by pollutant. Notes: Reduction in expected deaths per million population in a month.

Figure A7 shows the reduction in deaths from reduced electricity consumption at the PCA level. The spatial distribution depends on the reduction in electricity usage from COVID-19, the regional mix of fuels used to produce power, population exposure per ton of emissions, and demographics of the exposed population. These figures also illustrate that data are missing for a small number of counties. Table A4 shows the reduction in deaths aggregated to geographic regions based on a combination of ISO and NERC regions.

Table A4. Monthly reduction in deaths from electricity generation.

	Monthly Consumption (TWh)	Baseline Expected Deaths	Percent Electricity Reduction	Reduction in Expected Deaths	Reduced CO ₂ Emissions
Total	332.23	858.96	6.20	48.84	10.47
Southeast Utilities	54.98	170.77	8.91	13.13	2.55
Midwest Market	57.66	179.09	7.63	12.38	2.41
MidAtlantic Market	65.57	203.63	6.10	11.18	2.17
Southwest Market	22.54	69.99	6.11	3.92	0.76
Texas Market	31.97	54.30	6.66	3.29	0.92
New York Market	13.05	40.53	8.17	2.92	0.57
New England Market	9.77	30.34	5.32	1.43	0.28
California Market	18.17	15.42	7.61	1.02	0.56
Western Utilities	38.47	32.65	3.12	0.95	0.52
Florida Utilities	20.04	62.24	-1.97	-1.37	-0.27

Notes: California market is CAISO, Texas market is ERCOT, New England market is ISONE, Midwest market is MISO, New York market is NYISO, Mid-Atlantic market is PJM, Southwest market is SPP. For the others we aggregate PCAs by the NERC region: Florida (FRCC), Southeast (SERC), Western (WECC). Reduced CO₂ emissions in millions of metric tons.

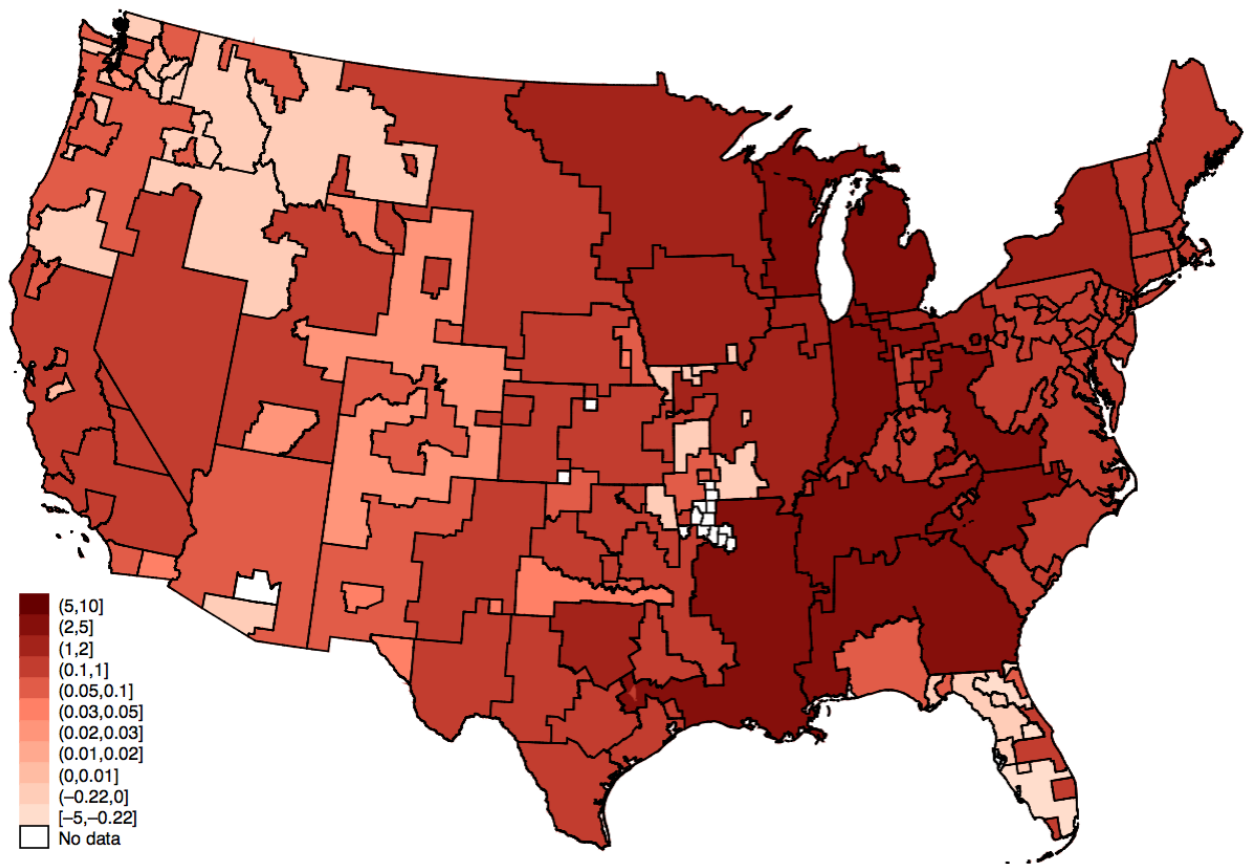


Figure A7. Reduction in deaths: electricity. Notes: Figure shows monthly reduction in expected deaths from reduced electricity consumption in each PCA.

Appendix A.5. COVID-19 Deaths and Total Respiratory Deaths

There are aspects of PM_{2.5} and COVID-19 that require an important qualification, or caveat, to our findings. The epidemiological literature that establishes the association between PM_{2.5} and premature mortality repeatedly finds that risk from exposure is proportional to baseline mortality rates [2,3]. Because of this, our benefit estimates may significantly understate actual benefits. The estimated ambient pollution reductions have occurred during a period of time when baseline risks are elevated. We modeled the link between emissions and monetary damages with data from the most recent year compre-

hensive economy-wide emissions data are available, the 2014 model year. If risk from exposure is proportional to mortality rates in a given period, then it is quite likely that exposure during a period when mortality rates are elevated will yield a larger relative risk. Thus, damages will be higher in the elevated risk period.

To gauge how large this effect might be we gathered daily COVID-19 mortality data. Figure A8 shows the monthly mortality rates for COVID-19 deaths and for total respiratory deaths from 2018 (the most recent year for which month-by-county data are available) across all counties in the contiguous U.S. It shows that risks are clearly elevated during the COVID-19 period from March and April 2020 [39]. The population-weighted average COVID-19 fatality rate in April of 2020 is approximately three-times larger than the respiratory cause mortality rate, in April of 2018. However, severe COVID-19 outbreaks are highly concentrated in a few counties. Figure A9 depicts these cases. The intent is to convey how much baseline mortality rates have changed due to COVID-19, and what that adjustment might mean for concurrent benefits from $PM_{2.5}$ reductions. The top-left panel shows the COVID-19 (April 2020) and respiratory (April 2018) rates for New York City. The difference in baseline risk is clear and extreme. Therefore, reductions in ambient $PM_{2.5}$ may be severely underestimated in this area. Detroit (top right) shows a more modest (though still five fold) difference. These comparisons in Los Angeles and San Francisco reveal much smaller differences.

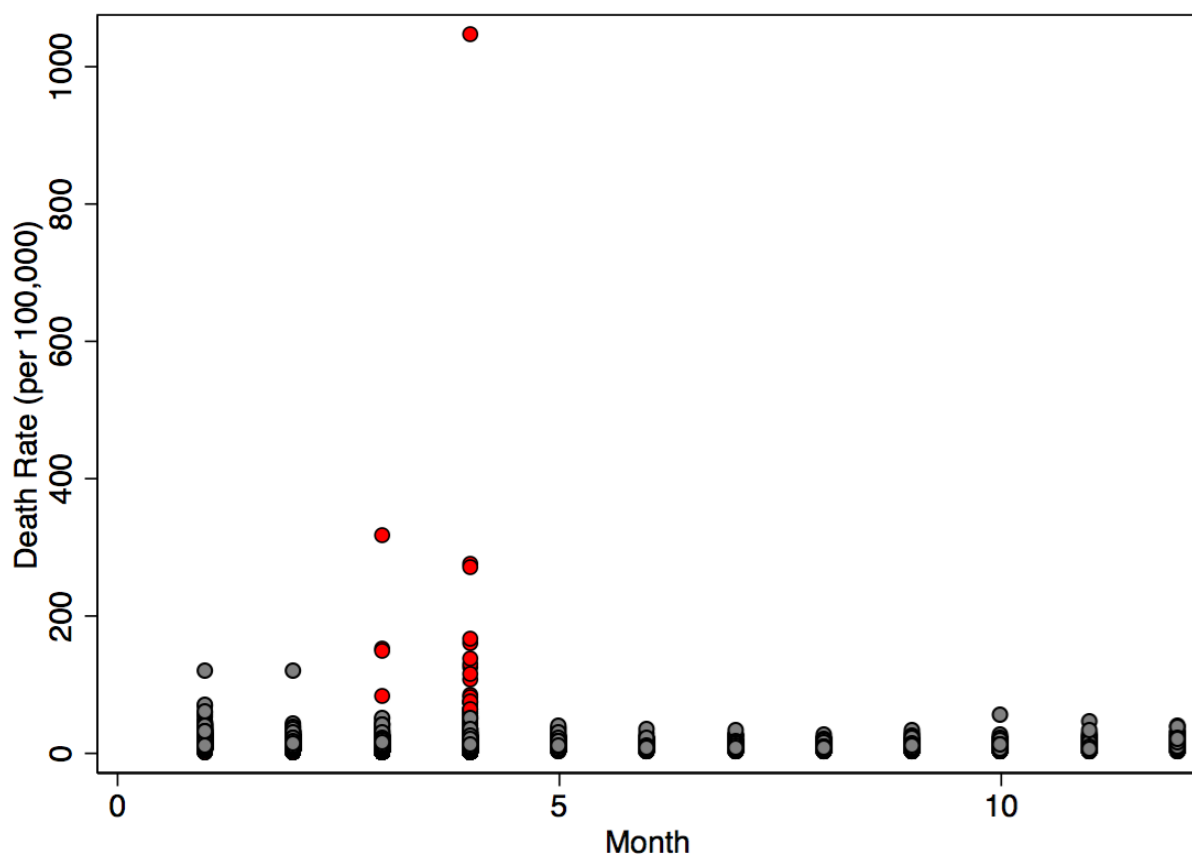


Figure A8. COVID-19 (2020) and total respiratory deaths (2018). Notes: Red indicates deaths due to COVID, black indicates all respiratory deaths. Each dot represents the deaths in a county for a given month. Source [39].

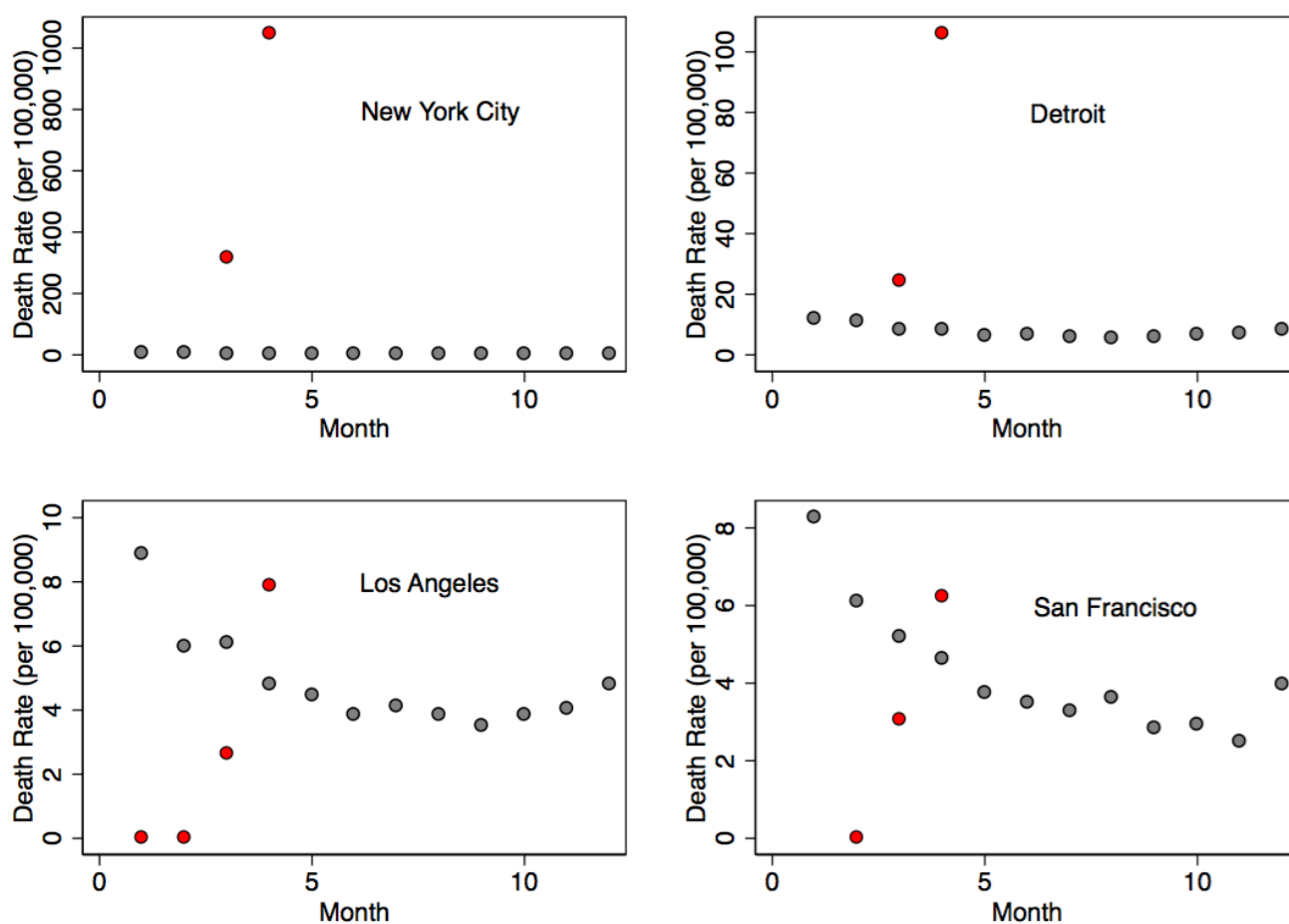


Figure A9. COVID-19 (2020) and total respiratory deaths (2018) in selected cities. Notes: Red indicates deaths due to COVID, black indicates all respiratory deaths. Source [39].

References

1. Brookings. Ten Facts about Covid-19 and the Economy. 2020. Available online: <https://www.brookings.edu/research/ten-facts-about-covid-19-and-the-u-s-economy/> (accessed on 5 January 2021).
2. Krewski, D.; Jerrett, M.; Burnett, R.T.; Ma, R.; Hughes, E.; Shi, Y.; Turner, M.C.; Pope, C.A., III; Thurston, G.; Calle, E.E.; et al. *Extended Follow-Up and Spatial Analysis of the American Cancer Society Study Linking Particulate Air Pollution and Mortality*; Health Effects Institute: Boston, MA, USA, 2009.
3. Lepeule, J.; Laden, F.; Dockery, D.; Schwartz, J. Chronic exposure to fine particles and mortality: An extended follow-up of the Harvard six cities study from 1974 to 2009. *Environ. Health Perspect* **2012**, *120*, 965–970. [[CrossRef](#)] [[PubMed](#)]
4. Muller, N.; Mendelsohn, R.; Nordhaus, W. Environmental Accounting for Pollution in the United States Economy. *Am. Econ. Rev.* **2011**, *101*, 1649–1675. [[CrossRef](#)]
5. Clay, K.; Jha, A.; Muller, N.Z.; Walsh, R. The External Costs of Shipping Petroleum Products by Pipeline and Rail: Evidence of Shipments of Crude Oil from North Dakota. *Energy J.* **2019**, *40*, 73–90. [[CrossRef](#)]
6. Holl, S.; Mansur, E.; Muller, N.; Yates, A. Are there environmental benefits from driving electric vehicles? The importance of local factors. *Am. Econ. Rev.* **2016**, *106*, 3700–3729.
7. Sexton, S.; Kirkpatrick, J.; Harris, R.; Muller, N. Heterogeneous Environmental and Grid Benefits from Rooftop Solar and the Costs of Inefficient Siting Decisions; NBER Working 2018, Paper Number 25241. 2018. Available online: <https://www.nber.org/papers> (accessed on 2 July 2021).
8. Hunt, A.; Boxell, L.; Conway, J.C.; Gentzkow, M.; Thaler, M.; Yang, D.Y. Polarization and Public Health: Partisan Differences in Social Distancing during the Coronavirus Pandemic; NBER Working Paper No. 26946. 2020. Available online: <https://www.nber.org/papers> (accessed on 2 July 2021).

9. Briscese, G.; Lacetera, N.; Macis, M.; Tonin, M. Compliance with COVID-19 Social-Distancing Measures in Italy: The Role of Expectations and Duration; NBER Working Paper No. 26916. 2020. Available online: <https://www.nber.org/papers> (accessed on 2 July 2021).
10. Fang, H.; Wang, L.; Yang, Y. Human Mobility Restrictions and the Spread of the Novel Coronavirus (2019-nCoV) in China; NBER Working Paper No. 26906. 2020. Available online: <https://www.nber.org/papers> (accessed on 2 July 2021).
11. Friedson, A.I.; McNichols, D.; Sabia, J.J.; Dave, D. Did California's Shelter-in-Place Order Work? Early Coronavirus-Related Public Health Effects; NBER Working Paper No. 26992. 2020. Available online: <https://www.nber.org/papers> (accessed on 2 July 2021).
12. Greenstone, M.; Nigam, V. Does Social Distancing Matter? Becker Friedman Institute for Economics Working Paper No. 2020-26; University of Chicago. 2020. Available online: <https://bfi.uchicago.edu/working-papers/> (accessed on 2 July 2021).
13. Muzammil, K.; Nasir, N.; Mahmood, S.E.; Hasan, A.U.; Alsabaani, A.A.; Ahmad, I.; Aggarwal, P.; Hussain, I.; Siddiqui, Z. Effects of COVID-19 Lockdown on Health—Two Sides of the Coin. *J. Evol. Med. Dent. Sci.* **2020**, *9*, 3998–4002. [[CrossRef](#)]
14. Brodeur, A.; Gray, D.; Islam, A.; Bhuiyan, S. A Literature Review of the Economics of COVID-19; IZA Discussion Paper 13411. 2020. Available online: <https://www.iza.org/publications/dp> (accessed on 2 July 2021).
15. Brodeur, A.; Cook, N.; Wright, T. On the Effects of Covid-19 Safer-at-Home Policies on Social Distancing, Car Crashes and Pollution; SSRN Scholarly Paper ID 3602431. 2020. Available online: <https://www.ssrn.com> (accessed on 2 July 2021).
16. Rebecca, T.-G.; Li, J.; Eilenberg, S.R.; Robinson, A.L.; Presto, A.A. Impacts of Modifiable Factors on Ambient Air Pollution: A Case Study of COVID-19 Shutdowns. *Environ. Sci. Technol. Lett. Artic. Asap.* **2020**. [[CrossRef](#)]
17. Andree, B. *Incidence of COVID-19 and Connections with Air Pollution Exposure: Evidence from The Netherlands*; World Bank Working Paper No. WPS9221; World Bank: Washington, DC, USA, 2020.
18. Skiriene, A.F.; Stasiskiene, Z. COVID-19 and air pollution: Measuring pandemic impact to air quality in five European countries. *Atmosphere* **2021**, *12*, 290. [[CrossRef](#)]
19. Almond, D.; Du, X.; Zhang, S. Did COVID-19 Improve Air Quality Near Hubei? NBER Working Paper No. 27086. 2020. Available online: <https://www.nber.org/papers> (accessed on 2 July 2021).
20. Han, Y.; Lam, J.C.K.; Li, V.O.K.; Guo, P.; Zhang, Q. The Effects of Outdoor Air Pollution Concentrations and Lockdowns on Covid-19 Infections in Wuhan and other Provincial Capitals in China. 2020. pp. 1–7. Available online: [Preprints.Org](https://preprints.org) (accessed on 2 July 2021).
21. He, G.; Pan, Y.; Tanaka, T. COVID-19, City Lockdowns, and Air Pollution: Evidence from China. *MedRxiv* **2020**. [[CrossRef](#)]
22. Silver, B.; He, X.; Arnold, S.R.; Spracklen, D.V. The impact of COVID-19 control measures on air quality in China. *Environ. Res. Lett.* **2020**, *15*. [[CrossRef](#)]
23. Dominguez-Amarillo, S.; Fernandez-Aguera, J.; Cesteros-Garcia, S.; Gonzalez-Lezcano, R.A. Bad air can also kill: Residential indoor air quality and pollutant exposure risk during the covid-19 crisis. *Int. J. Environ. Res. Public Health* **2020**, *17*, 7183. [[CrossRef](#)] [[PubMed](#)]
24. Sergi, B.; Muller, N.; Azevedo, I.; Davis, S. Regional and county flows of particulate matter damage in the US. *Environ. Res. Lett.* **2020**, *15*, 104073. [[CrossRef](#)]
25. Tschofen, P.; Azevedo, I.; Muller, N. Fine Particulate Matter Damages and Value Added in the United States Economy. *Proc. Natl. Acad. Sci. USA* **2019**, *116*, 19857–19862. [[CrossRef](#)] [[PubMed](#)]
26. Unacast. Social Distancing Scoreboard. 2020. Available online: <https://www.unacast.com/covid19/social-distancing-scoreboard> (accessed on 18 April 2020).
27. NTS. *National Transportation Statistics*; U.S. Department of Transportation, Bureau of Transportation Statistics: Washington, DC, USA, 2018. Available online: <https://www.bts.gov/content/estimated-national-average-vehicle-emissions-rates-vehicle-type-using-gasoline-and> (accessed on 18 April 2020).
28. BTS. Average Fuel Efficiency of U.S. Light Duty Vehicles. 2020. Available online: <https://www.bts.gov/content/average-fuel-efficiency-us-light-duty-vehicles> (accessed on 18 April 2020).
29. Cicala, S. Early Economic Impacts of COVID-19 in Europe: A View from the Grid; Mimeo. 2020. Available online: <https://epic.uchicago.edu/> (accessed on 2 July 2021).
30. Holl, S.; Mansur, E.; Muller, N.; Yates, A. Decompositions and Policy Consequences of an Extraordinary Decline in Air Pollution from Electricity Generation. *Am. Econ. J. Econ. Policy* **2020**, *12*, 244–274.
31. Jaramillo, P.; Muller, N.Z. Air pollution emissions and damages from energy production in the U.S.: 2002–2011. *Energy Policy* **2016**, *90*, 202–211. [[CrossRef](#)]
32. Muller, N.; Mendelsohn, R. Measuring the Damages Due to Air Pollution in the United States. *J. Environ. Econ. Manag.* **2007**, *54*, 1–14. [[CrossRef](#)]
33. EPA. The Benefits and Costs of the Clean Air Act from 1990 to 2020. 2011. Available online: https://www.epa.gov/sites/production/files/2015-07/documents/fullreport_rev_a.pdf (accessed on 2 July 2021).
34. Thunstrom, L.; Newbold, S.; Finnoff, D.; Ashworth, M.; Shogren, J. The benefits and costs of using social distancing to flatten the curve for COVID-19. *J. Benefit-Cost Anal.* **2020**, *11*, 179–195. [[CrossRef](#)]
35. EPA. Air Pollutant Emissions Trends Data. 2020. Available online: <https://www.epa.gov/air-emissions-inventories/air-pollutant-emissions-trends-data> (accessed on 18 April 2020).

-
36. Streetlight. VMT Monitor by County. 2020. Available online: <https://www.streetlightdata.com/vmt-monitor-by-county/> (accessed on 15 April 2020).
 37. EIA. U.S. Weekly Product Supplied. 2020. Available online: https://www.eia.gov/dnav/pet/pet_cons_wpsup_k_w.htm (accessed on 15 April 2020).
 38. EIA. Prime Supplier Sales Volumes. 2020. Available online: https://www.eia.gov/dnav/pet/pet_cons_prim_dcu_nus_m.htm (accessed on 2 July 2020).
 39. CDC. About Underlying Cause of Death, 1999–2018. Available online: <https://wonder.cdc.gov/ucd-icd10.html> (accessed on 1 April 2020).