

Brodeur, Abel; Cook, Nikolai; Wright, Taylor

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On the Effects of COVID-19 Safer-At-Home Policies on Social Distancing, Car Crashes and Pollution*

Abel Brodeur

Nikolai Cook

Taylor Wright

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Abstract

This paper investigates the impacts of COVID-19 safer-at-home policies on collisions and pollution. We find that statewide safer-at-home policies lead to a 20% reduction in vehicular collisions and that the effect is entirely driven by less severe collisions. For pollution, we find particulate matter concentration levels approximately $1.5\mu\text{g}/\text{m}^3$ lower during the period of a safer-at-home order, representing a 25% reduction. We document a similar reduction in air pollution following the implementation of similar policies in Europe. We calculate that as of the end of June 2020, the benefits from avoided car collisions in the U.S. were approximately \$16 billion while the benefits from reduced air pollution could be as high as \$13 billion.

KEYWORDS: COVID-19 - safer-at-home - lockdowns - air pollution - car crashes

JEL CODES: P48, Q53, Q58.

*Department of Economics, University of Ottawa, 120 University, Social Sciences Building, Ottawa, Ontario K1N 6N5, Canada. Brodeur: abrodeur@uottawa.ca. Cook: ncook@uottawa.ca. Wright: taylorjohn.wright@gmail.com. We thank Mohammad Elfeitori, Ramanvir Grewal and Kelly Liu for their excellent research assistance. We declare no conflict of interest and no research funding.

The emergence of COVID-19 (formally termed SARS-CoV-2 by the International Committee on Taxonomy of Viruses) has fundamentally changed human behavior. Characterized as a pandemic by the World Health Organization on March 11, 2020, the global scientific community is actively researching the virus and its impact. As of December 31, 2020, the United States has seen over 341 thousand deaths and over 19 million confirmed cases. COVID-19 has led most state governors to impose safer-at-home orders. We consider safer-at-home orders to be a blanket term that captures other efforts introduced simultaneously (or nearly so) whose goal was the suspension of economic activity and public interaction in an effort to “flatten the curve”.¹ To date, the focus of the debate over safer-at-home orders has been on their efficacy of transmission suppression and the implicit trade-off between lives saved and reduced economic activity. Safer-at-home orders have resulted in serious negative impacts on Americans in several dimensions: studies have shown large impacts on the labor market, mental health, and domestic violence incidents, for instance (e.g., [Adams-Prassl et al. \(2020\)](#); [Beland et al. \(2020\)](#); [Brodeur et al. \(2021\)](#); [Leslie and Wilson \(2020\)](#)).

In this paper, we study other potential *positive* externalities of safer-at-home orders; a decrease in air pollution and automobile collisions.² We rely on a difference-in-differences framework for identification. The setting is attractive for at least two reasons. First, not all states (nor all counties) implemented safer-at-home orders, and there is significant variation in implementation timing for those who do. Second, our identification strategy allows us to address issues of reverse causality and omitted variables bias by comparing states (or counties) that implemented safer-at-home orders at different points in time. Our identification assumption is that, conditional on COVID-19 incidence and other policies implemented (e.g., statewide face masks mandates), the difference in pollution (or automobile collisions) between areas with and without safer-at-home orders would be constant over time.

We first investigate the impact of safer-at-home orders on pollution. We find that state safer-at-home policies decreased air pollution (specifically PM2.5) by almost 25%, with larger effects for urban counties. This large effect size suggests that these policies reduce emissions by almost one half of a within-county standard deviation. Our estimates also suggest the issuance of a state order reduces the number of county-days with an acceptable PM2.5 level by around 10 percentage

¹See [Hsiang et al. \(2020\)](#) and [Sanga and McCrary \(2020\)](#) for similar treatment of safer-at-home orders and lockdowns.

²Researchers have also begun investigating the direct effect of air pollution on COVID-19. For example, higher levels of contemporaneous air pollution were associated with increased transmission and mortality in the Chinese context by [Zhang et al. \(2020\)](#). This correlation is also investigated for Italy, Spain, France, Germany, U.K. and U.S. in [Pansini and Fornacca \(2020\)](#). If this result were to hold in our context, the benefits of safer-at-home orders reducing air pollution may also include direct reductions in COVID-19 mortality and transmission.

points (nearly eliminating ‘polluted’ days). Further, we find that the decrease in air pollution persists for weeks after the order is lifted.

We check whether our results hold in a different setting by studying the impact of countrywide ‘lockdowns’ policies in Europe. More specifically, we build a data set of pseudo ‘counties’ for France, Germany, Italy, Spain, and the United Kingdom, and document a (temporary) decrease in air pollution following the implementation of lockdowns.

In addition, we estimate if there are car collision externalities stemming from the safer-at-home orders. We use daily-level traffic collision data for all counties, originally sourced through two real-time maps service API’s which draw from sources such as law enforcement and transportation departments. We identify a large reduction - about 20% - in traffic collisions after a state order is issued. We also examine their severity using a four-point scale index based on traffic flow/disruption. Following an order, we find a large and significant decrease in the most common types of collisions, with an increase in the minority of the most serious. Using social mobility data, we provide evidence that individuals shift their travel away from traditionally congested periods which helps explain the pattern of overall reductions but increases in collision severity.

We then explore the heterogeneous effects of safer-at-home policies on pollution and collisions across county characteristics. We find that the decline in pollution and collisions from safer-at-home orders is larger in urban counties. Our results also indicate that counties in states with a larger share of occupations that can be done remotely experience a larger reduction in pollution and collisions from these policies.

Lastly, we provide some back-of-the-envelope calculations of the estimated benefits from reduced pollution and collisions from safer-at-home orders. Using previous estimates of willingness to pay for pollution reduction from the U.S. we find the benefit from reduced pollution ranges from \$154 million to \$13 billion as of the end of June 2020. Using estimates of the societal cost of car collisions from the National Highway Traffic Safety Administration gives approximately \$16 billion in costs avoided as a result of safer-at-home orders as of June 2020.

We contribute to a growing literature informing the ongoing debate about safer-at-home orders (see [Brodeur, Gray, Islam and Bhuiyan \(2020\)](#) for a literature review). Previous studies have documented the positive impact of lockdowns on (preventing) COVID-19 incidence, but also their potential negative effects on the economy (e.g., [Kong and Prinz \(2020\)](#)), domestic violence (e.g., [Leslie and Wilson \(2020\)](#)), child maltreatment (e.g., [Bullinger et al. \(2020\)](#)) and mental health (e.g., [Adams-Prassl et al. \(2020\)](#)) among other socioeconomic dimensions. We contribute to this literature by pointing out two unintended benefits of lockdowns: decreased

car crashes and reduced air pollution.

The most relevant papers to ours are possibly [He et al. \(2020\)](#) and [Dang and Trinh \(Forthcoming\)](#). [He et al. \(2020\)](#) provide evidence that lockdowns in China decreased PM2.5 by approximately 25%. [Dang and Trinh \(Forthcoming\)](#) provide cross-national evidence for 164 countries on the impact of COVID-19 lockdowns on global concentration of NO₂ and PM2.5. They find that lockdowns decreased NO₂ and PM2.5 levels by about 5 percent. Other relevant work includes [Cicala et al. \(2020\)](#), [Graf et al. \(Forthcoming\)](#) and [Le Quéré et al. \(2020\)](#). [Cicala et al. \(2020\)](#) provide evidence that electricity consumption fell in the U.S. during the pandemic.³ [Graf et al. \(Forthcoming\)](#) investigate how lockdowns can affect electricity market performance using Italian data. [Le Quéré et al. \(2020\)](#) study the effects of government policies on country-level energy demand finding CO₂ emissions (estimated directly from confinement data) decreased by 17% compared to previous year levels. Our paper focuses on the immediate positive externalities from a reduction in road congestion and ambient particulate matter, using the available local and real time data necessary to understand how local and state government policies affect behavior.

The rest of the paper is organized as follows. Section 1 details the data, while Section 2 describes our identification strategy. We discuss the impacts of safer-at-home policies on pollution in Section 3. Section 4 investigates the effects of safer-at-home policies on collisions. In Section 5, we investigate the relationship between mobility and collision during safer-at-home orders. Section 6 provides our back of the envelope calculations of the positive externalities these policies. Section 7 concludes.

1 Data

In this section, we describe our data. We first provide information on COVID-19 cases and fatalities, and how they vary over time and across states. We then describe data sources for safer-at-home orders and other policies. Last, we describe our pollution and collision data.

1.1 COVID-19 Known Cases and Deaths

The first COVID-19 case in the U.S. was a man who had returned from Wuhan, China to Washington State. The case was confirmed on January 20, 2020. Six additional states confirmed cases later in January and February. The first case of community transmission was confirmed in California, on February 26, 2020. As of April 30, 2020 there were over 1 million confirmed cases due to COVID-19 in the

³[Leach et al. \(2020\)](#) document a reduction in the closely related Canadian context.

United States. On the last day of 2020, the CDC reported 19,663,976 total cases and 341,199 total deaths from COVID-19.

The COVID-19 known cases and deaths data comes from the Github repository associated with the Johns Hopkins University interactive dashboard. The data are available here: <https://github.com/CSSEGISandData/COVID-19>. Appendix Figures A1 and A2 illustrate the geographic distribution of COVID-19 known cases and deaths per 10,000 inhabitants, respectively.

1.2 Safer-at-Home Policy

Data for safer-at-home policies are from the *New York Times*.⁴ Figures 1 and 2 present maps indicating counties and states that implemented a safer-at-home policy prior to April 30, 2020, respectively. Nearly all states had implemented such a policy at this point in time, and the timing of implementation varies considerably. The first state to implement a safer-at-home policy was California on March 19th, 2020. 18 more states followed California in the following week. In 2020, 43 states (including the District of Columbia) had implemented some form of lockdown, representing 2,628 counties. Only California, North Carolina and Ohio had an active safer-at-home order on the last day of 2020. 148 counties implemented a county-level safer-at-home policy, of which 141 are located in states that would eventually have a statewide policy. The median county implemented its safer-at-home policy one week prior to the statewide policy.⁵

We also use data on the stringency of safer-at-home orders from the Oxford COVID-19 Government Response Tracker (OxCGRT) implemented by the University of Oxford’s Blavatnik School of Government. We rely on an ordinal scale measure of safer-at-home requirements, which takes the value of zero in the absence of an order, one if governmental authorities recommended a state to stay home, and two if staying-at-home was required with few exceptions such as daily exercise, grocery shopping, and essential trips.

1.3 Other Policies

We also gather data on the following COVID-19 statewide policies: day care closures, freezes on eviction, mandatory face mask policies, and mandated quarantine for individuals arriving from another state. Data on the implementation and duration of these policies come from Raifman et al. (2020). We provide more detailed information about these policies in the Appendix 7.1.

⁴Data are available at <https://www.nytimes.com/interactive/2020/us/coronavirus-stay-at-home-order.html>.

⁵Only seven counties (Brazos, Comal, Humboldt, Kings, Mendocino, Merced and Milam) implemented an additional safer-at-home policy after a statewide policy.

1.4 Social Distancing Data

We extract data on social distancing cell phone data from Unacast’s COVID-19 Toolkit. Unacast provides a Social Distancing Scoreboard at the county-level using cell phone data which aims to empower organizations to evaluate the effectiveness of social distancing initiatives (Brodeur, Grigoryeva and Kattan (2020)).

Using data pre-COVID-19 outbreak as a baseline, Unacast computes rate of changes in average distance travelled, non-essential visitation, and human encounters. For our analysis, we rely on the first index. Unacast’s data is available starting February 24th, 2020 and unavailable for many counties.

1.5 Air Pollution and Weather

1.5.1 Particulate Matter Concentrations Air pollution data is from *in situ* monitors and provided by AirNow, a partnership between United States agencies.⁶ The primary pollutant we use in our analysis is particulate matter with diameters less than 2.5 micrometers - particles small enough that they are capable of being inhaled and passing through the blood brain barrier. Emissions from combustion of gasoline, oil, diesel fuel or wood produce much of the PM2.5 pollution found in outdoor air. PM2.5 is associated with the greatest proportion of adverse health effects related to air pollution in the United States.

The Environmental Protection Agency monitors PM2.5 levels to protect public health and the environment, and has found average decreasing trends in the last two decades. From 1990 to 2016, PM2.5 measures had fallen around 25%, a reduction roughly equal to our estimated effect of the safer-at-home orders.

To aggregate PM2.5 levels from the monitor level to the county-level, we assign each county’s population weighted centroid to the three nearest air quality monitoring stations. Readings from each station are then averaged using inverse distance weights where closer monitors carry proportionally more weight in the pollution level. We also restrict our estimations to areas where the nearest station is within 50 kilometers (as accurate PM2.5 levels are necessarily local). In our sample, the minimum distance to a pollution monitoring station is 114 meters, while the mean and median are approximately 25km away.

In Appendix Figure A3, we present average weekly PM2.5 levels by county for the week of March 1-7, 2020. This period, prior to any safer-at-home policies serves as a visual representation of the geographic distribution of air pollution levels. In Appendix Figure A4, we present the same PM2.5 measures during the final week of

⁶The U.S. Environmental Protection Agency, National Oceanic and Atmospheric Administration (NOAA), National Park Service, NASA, Centers for Disease Control, and tribal, state, and local air quality agencies. The centralized system provides uniform quality control and reporting consistency.

April - after all eventually treated states had implemented a safer-at-home policy. See also Appendix Figure A5 for the distribution of PM2.5 concentrations for all county-days in our sample.

1.5.2 Other Air Pollution Measures While a derivative of PM2.5 levels, we also provide results using the Air Quality Index (AQI). This unit-less measure ranges from 0 to 500, with a score below 50 representing ‘not harmful’ levels of air pollution.

We also use aerosol optical depth (AOD) as an alternative and more geographically dispersed measure of air pollution. AOD estimates the amount of aerosol (tiny solid and liquid particles released by cars, industries, fires, etc.) present in the atmosphere and has been used as a proxy for surface air pollution (such as PM2.5). Technically, AOD measures the “extinction of a ray of light as it passes through the atmosphere” where extinction refers to diminishment either from absorption or scattering. A greater measure of AOD indicates a higher estimate of surface air pollution. Specifically, we use daily estimates of AOD at the $10\text{km} \times 10\text{km}$ resolution derived from the MODIS platform. We use pre-processed quality-controlled estimates which account for both low-quality measurements and highly reflective surfaces such as deserts.⁷ Appendix Figure A6 illustrates the distribution of AOD for all county-days in our sample.

1.5.3 Temperature and Precipitation For temperature and precipitation, we use the NOAA CPC Global Daily Temperature data set.⁸ This data set is typically used for verification of other temperature and precipitation products, and is available from 1979 to the present. This data set provides global coverage of temperature and precipitation at the $0.5 \text{ degree} \times 0.5 \text{ degree}$ spatial resolution. At the geographic center of the contiguous United States (39.83 North and 98.58 West), this represents a $55 \text{ km} \times 42 \text{ km}$ grid. This data set is typically available in real time. The underlying meteorological data comes from the Global Telecommunication System daily reports. They are from 6,000 to 7,000 global stations, with 10% of those in the United States. The station data is then gridded using the Shepard algorithm.

1.6 Collision Data

For our analysis on car crashes, we rely on collision data at the county-level from 49 states from January 1, 2020 to June 30, 2020 created by Moosavi et al. (2019).

⁷At the time of writing, the most recent data available for the AOD data was November 30, 2020, corresponding to day 335 of the year. AOD is not produced where clouds are definitively present. A quick guide to Aerosol Optical Depth can also be found from NOAA-NASA.

⁸NOAA stands for the National Oceanic and Atmospheric Administration, an American scientific agency within the United States Department of Commerce that focuses on the conditions of the oceans, major waterways, and the atmosphere. They manage the United States operational environmental satellites.

The data set is built from continuously streaming traffic data from MapQuest and Microsoft Bing map services and includes location, date, and severity of each crash. These services stream traffic incidents captured from national and state departments of transportation, law enforcement, traffic cameras, and traffic sensors. The authors of the data set collected data at 90 second intervals from 6am to 11pm and 150 second intervals from 11pm to 6am. Our main variable of interest is the daily number of collisions per county. The severity of an accident is coded as a number ranging from 1 to 4 with 1 being the smallest impact on traffic and 4 being a significant impact on traffic. Table 1 provides summary statistics for collisions. In our sample, there are about 1.8 collisions per day per county.

2 Identification Strategy

Our hypothesis is that safer-at-home policies decreased PM2.5 concentrations and collisions. To investigate this hypothesis, we estimate the following difference-in-differences specification:

$$y_{cst} = \alpha + \beta StateSafer_{st} + \lambda CountySafer_{cst} + \gamma_c + \delta_t + X'_{cst}\omega + \varepsilon_{cst} \quad (1)$$

where y_{cst} is, for instance, daily average PM2.5 measured in $\mu\text{g}/\text{m}^3$ in county c in state s and year t . We include a full set of county dummies γ_c to control for time-invariant county characteristics and calendar date dummies δ_t (e.g., a separate dummy for March 1, 2020, March 2, 2020, etc.). The time period spans January 1st, 2020 through the moment the statewide safer-at-home ended. We thus have an unbalanced panel of counties. For the bulk of our analysis, the sample is restricted to counties that eventually implement a county order or are under a statewide order. The last day in our sample is June 30th, 2020, although the sample ends prior to June 30th for the vast majority of counties. The state-level variable $StateSafer_{st}$ equals one once the state has implemented the order and zero for the pre-policy period.⁹ Our primary coefficient of interest is β . We also investigate the impact of county orders. The county-level variable $CountySafer_{ct}$ equals one once the county has issued the order and zero for the pre-policy period. Another coefficient of interest when included is thus λ . We cluster standard errors at the state-level, corresponding to the primary policy and treatment level.

Note that the adoption of safer-at-home policies and timing of adoption may be endogenously related to the severity of the virus. We thus include, X_{cst} , a vector of county-day level covariates including known COVID-19 cases and deaths per

⁹Using the date of announcement instead of the date of implementation yields similar conclusions. State orders are announced an average of three days prior to implementation.

10,000 inhabitants. County population data comes from 2019 Census estimates. We also control for county-day precipitation and average temperature. Further we include controls for the following statewide policies: day care closures, freezes on eviction, mandatory face mask policies, and mandated quarantine for individuals arriving from another state. The inclusion of these other policy variables help us to identify the impact of safer-at-home policies rather than the joint impact of multiple government interventions.

Our identification assumption is that, conditional on the included control variables, the evolution of PM2.5 concentrations or collisions for counties with safer-at-home policies would not have been different from those without the policies. This amounts to an assumption of parallel trends in PM2.5 or collisions for treated and untreated counties.¹⁰

Recent research on two-way fixed-effects (TWFE) estimators, which are usually motivated as difference-in-differences with multiple time periods, has identified issues that arise in the presence of heterogeneous treatment effects across groups or time (Callaway and Sant’Anna (Forthcoming), De Chaisemartin and d’Haultfoeuille (2020), Goodman-Bacon and Marcus (2020)). Using the `twowayfweights` Stata package detailed in De Chaisemartin and d’Haultfoeuille (2020), we document that 44% of the naive average treatments on the treated for pollution are assigned negative weights, indicating the need to reexamine our results using an alternative estimator. We use the alternative estimators provided by Callaway and Sant’Anna (Forthcoming), Callaway and Sant’Anna (2020) that are most appropriate for the staggered adoption of safer-at-home policies in our sample. We discuss these alternative estimates in section 3.¹¹

3 Safer-at-Home Orders and Pollution

In this section, we present the main results for air pollution using our difference-in-differences strategy. We then then provide additional results for Europe and heterogeneity analyses.

3.1 Main Results

In Table 2, we present our main result: a state’s implementation of a safer-at-home order significantly lowers air pollution in its constituent counties.

¹⁰In a further analysis presented in the Appendix, we check the robustness of our results using simulations constructed by applying synthetic control methods to match counties based on pre-policy pollution levels. Our results are quantitatively similar, and the corresponding placebos-in-place behave as expected.

¹¹We do not provide staggered adoption estimates for collisions as these estimators are not presently available for count data, however given that the share of negative weights is similar to pollution we are optimistic that they would behave similarly to those of pollution.

This table presents estimates of Equation 1 in which we compare counties in states with and without a statewide safer-at-home policy.¹² In all columns the dependent variable is PM2.5 concentration. We use a total of 1,592 counties in our estimation.

In the first column, we include only date and county fixed effects. The estimated reduction in PM2.5 from a statewide safer-at-home order is statistically significant at the 1% level and suggests that the introduction of a state order reduces PM2.5 levels by $1.7 \mu\text{g}/\text{m}^3$. With a mean of the dependent variable of $6.3 \mu\text{g}/\text{m}^3$ for the same time period one year prior, this suggests the policy decreased air pollution by more than 25%. For additional context, the within-county standard deviation of PM2.5 during the same period one year prior was $2.8 \mu\text{g}/\text{m}^3$, suggesting the policy reduces emissions by more than one *half* of a standard deviation.

In the second column, we include the county’s number of confirmed COVID-19 cases per 10,000 inhabitants as a control. In the third column, we include the county’s number of confirmed COVID-19 deaths per 10,000 inhabitants as a control. The inclusion of these two controls has almost no effect on the magnitude and significance of our estimates. The estimate for COVID-19 cases is negative and significant (statistically insignificant once we control for COVID deaths), suggesting that increased cases reduces PM2.5 in a county. In contrast, the estimate for COVID-19 deaths are not statistically significant.

In the fourth column, we control for four distinct statewide policies, while we add local weather conditions - temperature and precipitation - in the fifth column. Overall, the inclusion of other policies has little effect on the magnitude and significance of our state order estimates on PM2.5. The inclusion of weather controls makes the reductive effect of safer-at-home orders on air pollution smaller in magnitude, but the estimate remains large and significant. We note that temperature (precipitation) is positively (negatively) related to PM2.5 levels.

In Appendix Table A2, we test whether counties that implemented an order prior to a statewide order are differently affected than counties that did not implement an order. In columns 1 and 2, we reproduce our main result for all counties. Columns 3 and 4 restrict the sample to a subset of counties that issued their own orders prior to their respective state. In columns 5 and 6, we restrict the sample to counties that did not implement an order prior to the statewide order. Overall, we find that the decrease in air pollution following the implementation of a statewide order is large and significant for the two sets of counties. The estimate of the effect of a county order is negative, but barely statistically insignificant, suggesting that conditional on a state order being present, there is minimal *additional* reduction in PM2.5 from

¹²Our main results are robust to conducting the analysis at the state-level rather than at the county-level. See Appendix Table A1 for the estimates.

an additional county order being in effect.

In Appendix Table A3, we re-estimate the unweighted estimates from Table 2 and now weight by county population. In this manner, we place more emphasis on relatively more populous (and concurrently polluted) counties. The inclusion of this weighting increases the effect estimate by about 50% - the estimated reduction grows from 1.7 to 2.5 $\mu\text{g}/\text{m}^3$ - suggesting that the reduction in PM2.5 was larger for more populous counties.

3.2 Robustness Checks

In Table 3, we conduct a similar but distinct analysis. The column specifications and structure remains the same as in Table 2. While in Table 2 the dependent variable was PM2.5 concentration, in Table 3 the dependent variable is an indicator that takes a value of one if the PM2.5 level in that county, and on that day, is above the National Ambient Air Quality Standard of 12 $\mu\text{g}/\text{m}^3$.¹³ This reflects a change in interpretation from linear decreases in pollution concentration to decreases in exposure to environmental *hazards*. The interpretations of the coefficients change as well. For example, in column 1 nearly 90% of days prior to a state order have an acceptable level of ambient air pollution. Said differently, around one in ten county-days exceed the tolerable level set by the EPA. When state orders are introduced, almost all days for all counties have acceptably clean air (conditional on our control variables). The incremental addition of controls does not perturb this estimate significantly.¹⁴

Similarly, we rely on a remotely-sensed measure of air pollution in Appendix Tables A6 and A7; aerosol optical depth (AOD). AOD is a measure of the diffusion of light through the atmospheric column and a popular measure of air pollution which has the distinct advantage of being measured from space. Our main results (for example those presented in Table 3) are restricted to areas within 50 kilometers of an air pollution monitoring site, reflecting the concern that air pollution concentrations are inherently local. The locations of air quality monitoring sites are also most likely non-random to urban centers and, more recently, concerns of their strategic placement have also arisen. A uniformly measured and spatially available measure of air pollution found in aerosol optical depth does not suffer the same weaknesses, but does come with its own. For example, the relationship between

¹³The Environmental Protection Agency sets this standard as “Exposure to fine particle pollution can cause premature death and harmful cardiovascular effects such as heart attacks and strokes, and is linked to a variety of other significant health problems.” For example, [Bowe et al. \(2019\)](#) show that among a cohort of U.S. veterans, nine causes of death were associated with PM2.5 exposure above standards set by the Environmental Protection Agency.

¹⁴In Appendix Tables A4 and A5 we use instead Air Quality Index (AQI) and an indicator for an acceptable Air Quality Index of below 50, respectively. Estimates are substantively the same.

AOD and PM2.5 (and other pollutants) is often area-specific and can vary with surface albedo, making aggregation necessary in our setting, difficult. Lower AOD values are typically associated with lower levels of air pollution.

Appendix Table A6 uses aerosol optical depth as the dependent variable, but to maintain a comparison with our main estimates in Table 2, we restrict the sample to counties within 50 km of a monitoring station. In Appendix Table A7, we relax this restriction. The estimates presented in Appendix Tables A6 and A7 suggest that, during a lockdown, the measured within-county AOD is much lower (although imprecisely estimated), corresponding to reductions in air pollution.¹⁵ The main benefit of AOD over local PM2.5 concentrations is greater spatial availability. But one drawback is the use of particularly coarse readings from the MODIS-TERRA platform and the often relatively clean air in the United States (causing measures of AOD to be often missing). Of course, there is also the possibility that air pollution above the surface level is also being measured.

Appendix Table A8 provides the three aggregated alternative TWFE estimators described in Callaway and Sant’Anna (Forthcoming). Column 1 recreates the estimate from column 1 of Table 2. Column 2 provides the weighted (by group size) average of all estimated county-day average treatment effects. In column 3, we provide the average treatment effect over all lengths of exposure to safer-at-home orders, while column 4 provides the average effect of implementing a safer-at-home order for counties that were under an order in any period. All columns include county and date fixed effects. These alternative estimators confirm that safer-at-home orders have a negative and statistically significant effect on PM2.5.

3.3 Graphical Evidence

We provide a visual representation of the reduction in pollution from the implementation of a safer-at-home order in Figure 3.¹⁶ This figure plots estimated PM2.5 levels at daily intervals pre- and post-statewide order. The associated equation is:

$$y_{cst} = \alpha + \sum_{n=-40}^{100} \beta_n(DaysSinceLockdown = n) + \gamma c + \delta_t + X'_{cst}\omega + \varepsilon_{cst} \quad (2)$$

This specification decomposes the level of PM2.5 by the number of days before and since the state order. The regression includes county and date fixed effects in addition to our full set of weather and policy controls. We plot the estimated

¹⁵Of note, once we add precipitation as a control, the point estimate becomes positive for the restricted sample. This is potentially due to the fact that precipitation could affect the estimates of AOD by inadvertently removing days with haze mistaken for cloud cover.

¹⁶See Appendix Figure A7 for leads and lags of the dependent variable Air Quality Index (AQI).

difference between PM2.5 levels compared to the date that the state order was implemented (which is set to zero). The time window is 40 days before to 100 days after the policy is implemented. The dashed lines represent robust 95% confidence intervals.

Figure 3 shows that PM2.5 levels, within-county and conditional on our covariates, were relatively stable from 40 days before up to the implementation of the statewide order. We begin to see a slight reduction in PM2.5 emissions once the order is implemented, with a much steeper decrease in the weeks following implementation. The negative impact is at its largest at the end of the time window, suggesting that a safer-at-home order’s impact on air pollution persists in the weeks following the moment orders are lifted (i.e., all lifted after day $(t+80)$).

3.4 Strictness of Order and Heterogeneity Analyzes

In Appendix Table A9, we test whether the estimated air pollution reduction during a safer-at-home order is related to the strictness of the order. Our variables of interest are dummies for “low” safer-at-home order intensity and “high” safer-at-home order intensity. Our estimates show that higher intensity orders are associated with a larger decrease in air pollution than lower intensity orders. This result has important policy implications since the strictness of orders may be related to many factors such as economic losses and mental health distress.

We investigate whether the magnitude of the documented effect of safer-at-home policies on pollution is related to county-level characteristics in Appendix Table A10. More precisely, we test whether more urban, younger, and Democrat counties experienced a larger decrease in PM2.5 following the implementation of a safer-at-home order.¹⁷ In columns 1 and 2, we split the sample for over and below county urbanization of 50%, respectively. We find that the estimated decrease is about 25% larger for urban counties than rural counties, confirming our previous finding that more populous counties are more affected by state orders.

In columns 3 and 4, we restrict the sample for counties in which a majority of voters voted for President Trump during the 2016 Presidential Election. Column 4 restricts the sample to the other counties. We find that the decrease in pollution is much smaller in counties that supported President Trump in 2016. This finding is in line with Engle et al. (2020), who document that counties with a lower share of votes for Republicans comply more with safer-at-home orders. We confirm this pattern in Appendix Table A11. Of note, we find that ‘Trump’ counties are also different in many other aspects that may be correlated with the ability to reduce

¹⁷Data on the share of urban population is based 2010 Census data. Urbanization rate comes from the American Community Survey (ACS-5 years estimates).

emissions. Readers should therefore be careful when interpreting the findings of this heterogeneity analysis.

Column 5 (6) restricts the sample to counties with relatively more (less) individuals aged at least 65 years old (split by median). We find that counties with relatively more young people experienced a larger decrease in PM2.5, perhaps due to more work being done remotely during-lockdown.

We explore this possibility in columns 7 and 8. We split the sample into counties within states which have above and below median shares of occupations that can be done from home. These classifications of the feasibility of working from home in a given occupation come from [Dingel and Neiman \(2020\)](#) and associated coding provided by those authors and Ole Agersnap. Column 7 (8) corresponds to counties in states with an above (below) median share of occupations able to be done from home. We find that counties in states with a greater ability to work from home experience a slightly larger decrease in PM2.5.

3.5 Europe

We now explore the impact of countrywide lockdowns on pollution in Western Europe. This exercise serves at least two purposes. First, examining the European case is worthy of study in itself. Second, it serves as a test of external validity for our U.S. results. At the time of writing, some form of lockdown had been applied to the residents of most European countries - we focus on France, Germany, Italy, Spain, and the United Kingdom, the largest countries in Europe by population.

For this analysis, we examine how national-level orders affected PM2.5 concentrations at the sub-national level. We divided each country into administrative units at a similar administrative level to United States counties for comparability. A total of 841 areas are used with 96 from France (roughly corresponding to départements), 403 from Germany (roughly corresponding to kreise), 113 from Italy (roughly corresponding to provinces), 55 from Spain (roughly corresponding to provinces) and 192 from the United Kingdom (roughly corresponding to counties).

Air pollution data was provided by the European Environmental Agency. Pollution remains measured in $\mu\text{g}/\text{m}^3$ at the population-weighted centroid for each administrative unit (determined in [Hall et al. \(2019\)](#)). The mean PM2.5 concentration during the period is $8.7\mu\text{g}/\text{m}^3$, and the within-unit standard deviation is 6.0. Temperature and precipitation use the same dataset from our U.S. estimates.

Data on lockdowns come from the Coronavirus Government Response Tracker produced by the University of Oxford. This dataset tracks worldwide national (and in rare cases) subnational government responses to the COVID-19 pandemic. We chose this data set because of its uniform coding over the different countries we ex-

amine, and a centralized and curated count of confirmed cases and deaths. Further, the uniformity of the mask mandate, quarantine mandate and school closures coding between countries is also valuable. The main drawback to this data set is that the government response, cases, deaths, and policy variables are at the national-level.

Our main results for Europe are presented in Table 4. The dependent variable in all columns is PM2.5 measured in $\mu\text{g}/\text{m}^3$. We control for the number of COVID-19 cases and deaths at the national-level. The estimate for our countrywide lockdown is statistically significant at the 1% level and suggests that the introduction of a lockdown reduces PM2.5 levels by about $1.7 \mu\text{g}/\text{m}^3$ in our preferred specification. The mean of the dependent variable for pre-lockdown days is about $10.7 \mu\text{g}/\text{m}^3$, suggesting that European lockdowns decreased air pollution by about 16%.

We also document the effect of lockdowns for each country separately in Appendix Table A12. Our country-level controls are necessarily dropped for this analysis since we estimate the effect of a national lockdown for each of the countries separately. We find large and significant reductions in air pollution for all five countries.¹⁸

Last, in Appendix Figure A8, we present our leads and lags estimates for Europe, using the specification which decomposes the level of PM2.5 by the number of days before and since the national order. Following a lockdown, we see a general reduction in air pollution levels. This (admittedly messy) trend continues downward for approximately 15 days before reversing slowly and returning to pre-order levels around 75 days after the initial lockdown is released. This return to normal levels and its ‘spiky’ estimation likely reflects both underlying heterogeneity in strictness of orders and different country implementation and lifting of orders.

4 Safer-at-Home Orders and Collisions

We now present the main results for collision. Safer-at-home orders are implemented primarily to save lives by limiting the spread of the virus through social distancing, non-critical business closures, and restriction to only necessary activities. As a by-product, these orders can also result in fewer vehicles on the road—directly reducing air pollution, collisions, and perhaps even fatalities. As motor vehicle collisions are one of the leading causes of deaths for Americans, these unintended benefits would suggest that the number of lives saved by safer-at-home orders may be more than expected.¹⁹

¹⁸Of note, we document that Germany’s partial order also led to a large decrease in air pollution, potentially suggesting that the stringency of lockdowns might not be related to the decrease in PM2.5 concentrations. See Brodeur et al. (2021) for more details on the stringency of European lockdowns.

¹⁹Deaths from motor vehicle collisions are surpassed only by heart disease, malignant neoplasms, and unintentional poisoning (both heart disease and malignant neoplasms have been connected to

4.1 Main Results

In Table 5, we estimate the effects of state orders on the collision incidence rate in a county, per day.²⁰ We present the incidence-rate ratios of a Poisson count model with county and date fixed effects; an estimate below one is a reduction in the dependent variable. The time period is January 1st, 2020 through the moment the statewide safer-at-home order ends.²¹ The structure of the table is the same as Table 2.

In the first column, we estimate that a state order reduces the incidence of collisions by 16%.²² In columns 2–3, we introduce the number of COVID-19 cases and deaths, respectively. Regardless of the underlying severity of the infection, the effectiveness of the state order remains large and statistically significant. In the fourth column, we introduce the set of other policies, while column 5 adds weather controls.²³ Introducing these additional variables in the model decreases the size of the coefficient (i.e., increases the decrease in car collision) and has no effect on the significance of the estimates. In column 5, the estimate suggest that safer-at-home orders decrease daily collisions by 20%. As there are approximately 1.4 collisions for treated counties per county and per day during the safer-at-home order, this reduction implies a counterfactual of about 1.7 collisions results in a reduction of 0.35 collisions per day *per county*.

In Appendix Table A14, we repeat the analysis presented in Appendix Table A2 and test whether counties that implemented an order prior to a statewide order are differently affected than counties that did not implement their own order. The estimate suggests that safer-at-home orders decrease car collisions for both sets of counties with a slightly larger decrease for counties that implemented an order prior to the statewide order. In addition, we find that conditional on the presence of a statewide order, county orders also statistically significantly decrease collisions. The estimated negative effect of a county order is equal to that of the statewide order, suggesting that counties also have the ability to significantly reduce collisions by issuing safer-at-home orders, even when under the influence of a statewide order.

To sum up, we find that state and county orders significantly decrease collisions. This result is quite important given the large number of car crash fatalities in the PM2.5 exposure).

²⁰See Appendix Table A13 for the analysis at the state-level rather than at the county-level. Our conclusions remain unchanged.

²¹The sample includes 1,711 counties. Counties with no collisions during the entire time period are excluded from the sample.

²²Figure 4 confirms this pattern. This figure plots regression coefficients for collisions corresponding to number of days before/after state order issued.

²³Precipitation increases daily collisions in our sample, while higher maximum temperature is associated with fewer collisions - unsurprising when the sample period assigns rising temperatures to coming out of winter rather than entering into the hottest months of summer.

U.S. (about 35,000 in 2016).

4.2 Graphical Evidence

We provide a visual summary of the collision impact in Figure 4. This figure is similar to Figure 3 and plots the estimated collision levels at daily intervals pre- and post-statewide order (as in equation 2). Our estimates are not statistically significant from 40 days to a few days prior to the implementation of the order. There is a small increase in collisions a few days prior to the implementation of the order, perhaps due to growth in traffic for last minute shopping. Then we document a large decrease in collisions during safer-at-home orders, with the largest estimated coefficients from 45 to 80 days post-order. In other words, collisions are significantly reduced for as long as safer-at-home orders are in place. Once orders start to be lifted (i.e., all lifted after day $(t+80)$), the effect of the order on collision decreases in magnitude and becomes insignificant around 95 days after the order. These results suggest that orders do not have persistent effect on collisions.

4.3 Severity of Collisions

We now turn to the impact of safer-at-home orders on the severity of collisions. The severity of each collision is coded based on traffic flow/disruption and graded from one to four by the data providers. A value of one indicates a short delay as a result of the accident while a four indicates a significant impact on traffic, i.e., a long delay. Before the order period, the least common category of collision was the least severe. During the order period, the least common category was the most severe. During both periods, the most common severity of a collision is category two.

The estimates are presented in Table 6. All columns include our full set of controls. Column 1 reproduces our main results for any of the collision severities, while columns 2–5 look at the impact of state-wide orders on each of the four severity categories, respectively. The number of counties varies across columns since counties with no collisions in a given severity category are omitted.²⁴ Our estimates suggest that statewide safer-at-home orders significantly decreased collisions of severity one and two, by 14% and 23% respectively. There is no effect for the second-to-most severe crashes. Interestingly, we document increases in the most severe type of collisions, with an increase of 18% (a large percentage increase, however, this increase is relative to a small baseline). This result is in line with the idea that some drivers might be speeding more during lockdowns, which could lead to an increase in severe (and often fatal) collisions.

²⁴See Table 1 for summary statistics.

4.4 Strictness of Order and Heterogeneity Analyzes

We now check whether more stringent safer-at-home orders lead to a greater decrease in collisions than orders simply recommending to stay home. The estimates are presented in Appendix Table A9, columns 3 and 4. Again, our variables of interest are dummies for “low” safer-at-home intensity and “high” safer-at-home intensity. Our estimates show that both types of orders lead to a decrease in collisions of about the same magnitude.

Appendix Table A15 provides the heterogeneity analysis by county characteristics. The structure of this table is similar to Appendix Table A10. We find that the decrease in collisions is driven entirely by urban counties, with a significant decrease of about 23% in daily collisions. By political divide, we also find that counties that supported President Trump in 2016 have a smaller reduction in collisions than those who did not. By resident age, the difference seems to be small. We find that the decrease in collisions is very large and significant for counties in states with above median shares of occupations that can be done remotely, while the estimate is slightly greater than one (corresponding to an increase in collisions) for counties below the median shares.

To sum up, our results suggest that the documented decrease in collisions does not persist over time, is driven by urban counties, counties with lower support for President Trump, and counties in which workers are more able to work remotely.

5 Stay-Home Orders, Social Distancing and Collisions

We now investigate one of the mechanisms through which safer-at-home policies might have impacted car collisions; changes in social distancing behaviors. For this analysis, we rely social distancing cell phone data from Unacast.

We proceed in three steps. First, we note that a large number of studies have documented the impacts of safer-at-home on social mobility, including our own working paper Brodeur, Cook and Wright (2020). See, for instance, Brodeur, Grigoryeva and Kattan (2020) and Cicala et al. (2020) who rely on Unacast data and provide evidence that safer-at-home policies decreased total distance traveled.²⁵

Second, we test whether safer-at-home orders changed the daily distribution of car collisions. In other words, we want to explore whether or not the change in collisions caused by safer-at-home orders is partly coming from a change in the timing of travel (and therefore a change in the relative congestion levels of different times of day) rather than entirely due to reductions in travel. In addition this may have

²⁵This relationship has also been shown by Google back in April 2020 (see <https://www.theverge.com/2020/4/3/21206318/google-location-data-mobility-reports-covid-19-privacy>).

implications for the composition of collisions in terms of single or multiple vehicles involved. Figure 5 illustrates the distribution of collisions across all hours of the day for our sample period and the corresponding time period in 2019. We find that the timing of collisions changed in 2020 in comparison to 2019, with more collisions in 2020 occurring during the afternoon and less during the night and early rush hour. A large literature documents a positive or concave relationship between traffic/congestion and car crashes (e.g., Gwynn (1967); Head (1959); Schoppert (1957); Zhou and Sisiopiku (1997)). See Retallack and Ostendorf (2019) for a literature review. It is posited that this relationship could be a result of aggregating single vehicle and multi-vehicle collisions where single vehicle collisions are high during periods of little congestion and multi-vehicle collisions are high during periods of high congestion. As safer-at-home orders increase work from home and decrease mobility, we should expect to see less congestion and as a consequence fewer collisions during the typical rush hour periods. Similarly, as individuals now have more flexibility in their schedules, we might expect trips to be displaced across hours of the day rather than eliminated entirely and as a consequence we should expect an increase in fatal collisions. While we do not observe collision fatality directly, we do provide evidence of increased collision severity as measured by traffic delays in Table 6. Overall, these findings provide suggestive evidence that the increase in more severe collisions during safer-at-home orders is partly due to a shift in the distribution of traffic (and therefore congestion) across hours of the day.

Third, we document the relationship between travel distance and collisions by exploiting large variation in mobility due to safer-at-home orders. As the typical structure of work days and commutes was significantly altered by safer-at-home orders, it is possible that the positive or concave relationship between congestion/traffic and collisions no longer holds while they are in effect. While social mobility data does not provide direct evidence of congestion, we can use this data to explore the suggestive evidence of the relationship between travel and collisions using the exogenous variation in traffic from safer-at-home orders. However, we are unable to say anything about the concave nature of the relationship using our empirical strategy.

To attempt to achieve exogenous variation of mobility at the county-level, we instrument travel distance with statewide safer-at-home orders. The rationale for the instrument is that statewide orders led to a large decrease in mobility, which we exploit to document the relationship between mobility and collisions.

More precisely, we estimate:

$$\begin{cases} Travel_{cst} = \rho + \phi \cdot StateSafer_{st} + X'_{cst}\psi + \theta_c + \kappa_t + \nu_{cst} \\ Y_{cst} = \alpha + \delta \hat{Travel}_{cst} + X'_c\gamma + \theta_c + \kappa_t + \varepsilon_{cst}, \end{cases} \quad (3)$$

where $StateSafer_{st}$ equals one once the state has implemented the order and zero for the pre-policy period. We run a first stage in which we regress this variable on the travel distance at the county-level, including all controls and fixed effects as in Equation 1. Then we plug in the predicted values of this first stage and estimate the second stage of the 2SLS. The dependent variable in the second stage is the number of traffic collisions. The time period is March 1st, 2020 through the moment the statewide safer-at-home ended.

For our instrument to be valid two conditions have to hold. First, our instrument has to be a strong predictor of travel distance. As mentioned before, a large literature showed that statewide safer-at-home orders significantly decreased mobility. The F-statistic for the first stage is about 1733 confirming the strong negative impact of orders on mobility.

Second, in order for our instrument to allow a causal interpretation, statewide orders must only affect the number of collisions through its effect on social mobility, i.e., the exogeneity assumption. We believe this condition is unlikely to hold in our setting given the documented effect of lockdowns on economic activity and other socioeconomic variables. This is an issue in our setting since it is plausible that labor force status and work arrangements are related to driving behavior. Nonetheless, we proceed with our 2SLS exercise, but caution readers that the exclusion restriction is likely violated.

Table 7 presents our estimates of Equation 3. Column 1 is for all counties, column 2 corresponds to majority urban counties, and column 3 to majority rural counties. The estimate in column 1 suggests that a 100% increase in travel distance relative to the baseline period is associated with 4 additional car collisions per county-day. The estimate is statistically significant at conventional levels. The estimate in column 2 is also statistically significant and suggests a 100% increase in travel distance relative to the baseline period is associated with just over 9 additional collisions per county-day in urban counties. Meanwhile, we find no evidence that changes in travel distance induced by safer-at-home orders reduce collisions in rural counties. Taken together, these findings provide suggestive evidence that the reduction in collisions stemming from safer-at-home orders is being modulated through mobility and is driven by urban counties rather than rural counties. Consistent with the existing literature, the positive relationship between congestion (proxied for by travel distance) and collisions remains during the COVID-19.

To summarize, we argue that safer-at-home orders led to a decrease in social mobility and a shift in the timing of traffic away from traditionally congested periods, and show suggestive evidence that these are two of the main driving forces behind the observed reduction in collisions and increase in collision severity.

6 Interpretation

In this section, we provide back-of-the-envelope calculations of the benefits from *positive* pollution and collision externalities generated by safer-at-home orders. Our calculations here are, in part, based on the growing literature estimating the revealed - rather than stated - willingness to pay (WTP) for air quality. It is also important to note that most studies do not provide estimates of the WTP for temporary reductions in air quality, but instead attempt to identify the WTP of a permanent reduction in pollution. This means that our calculations are based on the assumption that individuals value a temporary abatement at the average annual value of a permanent reduction pro-rated for the duration of the abatement period, in this case the duration of the safer-at-home order. Note that these calculations ignore possible WTP increases for clean air during COVID-19, as recent research has begun to identify increased mortality from and transmission of the virus with higher levels of contemporaneous air pollution (Zhang et al. 2020, Pansini and Fornacca 2020).

We first review the literature. Currie et al. (2015) exploit the effect of toxic plant openings to estimate the impact of air quality on American house values and birth weights. They find an 11% reduction in house values and a 3% increase in low birth weights in nearby households. Recent work by Ito and Zhang (2020) using purchases of air purifiers in China suggests that the mean WTP for 1 $\mu\text{g}/\text{m}^3$ reduction of PM10 is 1.34 USD annually - and increases strongly with household income. For a household making 10,000 USD per year (the upper limit of the sample), they estimate a marginal willingness to pay of 5 USD per 1 $\mu\text{g}/\text{m}^3$ PM10. Chay and Greenstone (2005) study housing price evolutions in the 1970's and '80s in American counties that were quasi-randomly assigned federally mandated air pollution regulations. They find that a one unit decrease in particulates (all suspended particulates - what was targeted by the regulations) results in a 0.7 to 1.5 percent increase in house values. Deschênes et al. (2017) quantify the defensive investment portion of willingness to pay for air pollution reduction to be around one third - and that nitrogen oxide reduction program benefits 'easily' exceed costs. Barwick et al. (2017) estimate that the lower bound of the annual WTP for a 10 $\mu\text{g}/\text{m}^3$ reduction in PM2.5 is 9.25 USD per Chinese household, or 7% of total healthcare spending. Finally, Bayer et al. (2016) estimate the WTP to avoid ozone using house purchases in the San Francisco Bay Area, finding a 10% reduction in pollution commanded a price almost equal to a 10% reduction in violent crime.

We now turn to our back-of-the-envelope calculations. To calculate these, we first rely on estimates from the U.S. to compute the WTP associated with our estimated 7%–25% reduction in PM2.5. We then scale the estimates to the duration

of each state’s safer-at-home order and aggregate over the number of households in the state (drawn from the 2018 American Community Survey) before finally aggregating WTP over all states implementing policies.

Recall that our estimates from Table 2 indicate that the introduction of safer-at-home orders decreased pollution by about $1.4 \mu\text{g}/\text{m}^3$ while Appendix Table A8 provides an estimate of $0.4 \mu\text{g}/\text{m}^3$. We also note that Bayer et al. (2016) find that American home owners are willing to pay between about 300 USD annually for a 10% reduction in one pollutant; the WTP associated with our estimated 7%–25% reduction in PM2.5 could thus be as high as 210–750 USD annually per household.²⁶ Using WTP estimates from the most appropriate American samples, we find estimated benefits of 154 million to 500 million USD using the adapted WTPs from Bayer et al. (2009) (who estimate that the marginal WTP for an annual $1 \mu\text{g}/\text{m}^3$ reduction in PM10 for United States metropolitan areas to be 22 USD per household), and 3.6 billion to 13.1 billion USD using the adapted estimates from Bayer et al. (2016). These estimates vary widely, no doubt due to the many assumptions necessary to compute figures at the aggregate level. However, they serve to give a sense of the order of magnitude of the possible environmental benefits these orders have.

There are also extensive costs associated with traffic collisions, from congestion impacts; to medical and repair bills; to loss of life. We generate rough estimates of the benefits of reduced collisions using the National Highway Traffic Safety Administration’s (NHTSA) estimates that the average cost of collisions in 2013 was 17,794 USD (2010, 21,054 USD in 2020) per crash.²⁷ When accounting for quality-of-life valuations, the estimates are an average of 61,470 USD (2010, 72,732 USD in 2020) per crash.

Our estimates in Table 5 suggest a reduction in collisions of 20%. The mean number of crashes during safer-at-home orders among treated counties was 1.4 crashes per day, implying that the counterfactual crash rate would have been about 1.77 crashes per day per county. Applying our estimates to the 124,370 county-days spent under safer-at-home policies suggests that over 219,000 collisions may have been avoided by June 30th, 2020. Using the numbers from the NHTSA gives approximately 15.9 billion 2020 USD in costs avoided as a result of safer-at-home orders over that period.

A major limitation is that our estimates in Table 6 suggest that we actually see an increase in more severe collisions while the average effects are driven by reduc-

²⁶While this may seem large, classical estimates from Harrison and Rubinfeld (1978) using data from the Boston Area following the *Clean Air Act* placed a WTP for a 25% reduction in air pollution at approximately 2,000 (1978 USD). Other WTP estimates discussed in Chattopadhyay (1999) for particulate pollution reductions in the Chicago Area up to 366 USD in 1982-84 dollars.

²⁷See <https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812013>.

tions in less severe collisions. This means that our back-of-the-envelope calculations may overestimate the costs of collisions as while the volume of crashes is declining, the fatality rate may not be. Unfortunately, our data do not contain information about fatalities directly and therefore do not allow us examine the extent to which this could be true.

7 Conclusion

In many respects, safer-at-home policies have been expected and shown to have negative impacts on societies by, for instance increasing mental health distress and exacerbating the economic impacts of COVID-19. This paper represents a first step toward understanding some of the unintended *positive* effects safer-at-home policies have on pollution and car crashes.

We rely on a difference-in-differences framework with high frequency air pollution data and daily collision data. We find that statewide safer-at-home policies lead to a 25% reduction in PM2.5 concentrations and a 20% reduction in vehicular collisions; one of the leading causes of death in the United States. We also provide suggestive evidence that the reduction in collisions is driven in part by reduced travel associated with safer-at-home orders and by distributional changes to traffic times that also explain the increase in collision severity. We calculate that over 219,000 collisions may have been avoided by June 30th, 2020, which translates to approximately \$16 billion in costs avoided. The benefits from reduced air pollution could range from \$154 million to \$13 billion.

Our paper raises broader questions of the nuance involved in estimating the costs and benefits of safer-at-home policies. As more data on COVID-19 cases and deaths became available, it was possible to better estimate how many lives were saved ([Hsiang et al. 2020](#)). But the unintended economic consequences and large sphere of domains impacted by safer-at-home orders make it a difficult, but worthwhile, task to estimate the full set of costs and benefits of these policies.

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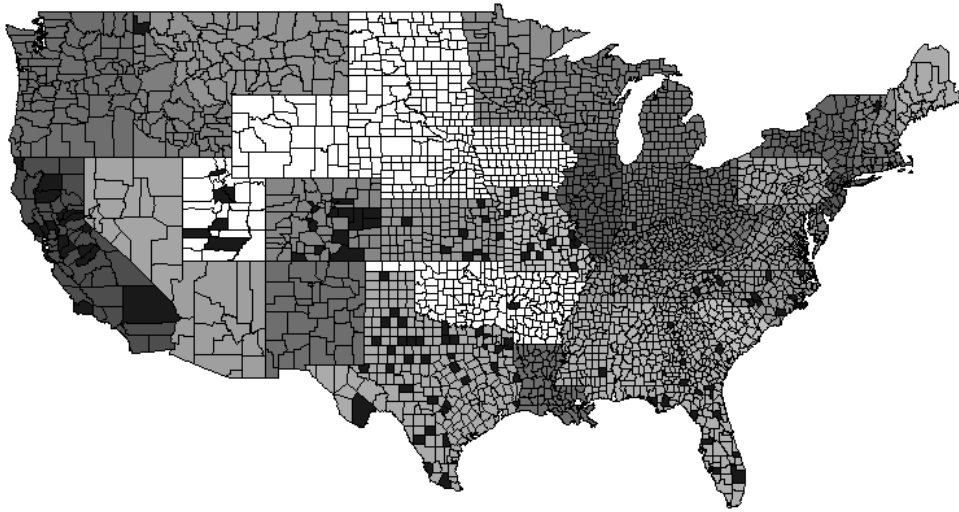
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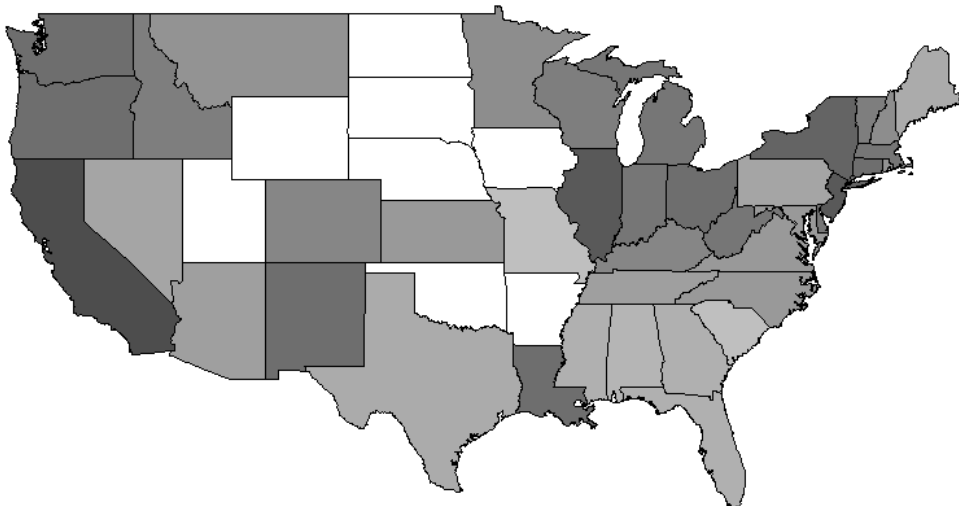
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Figure 1: Counties that Issued an Order



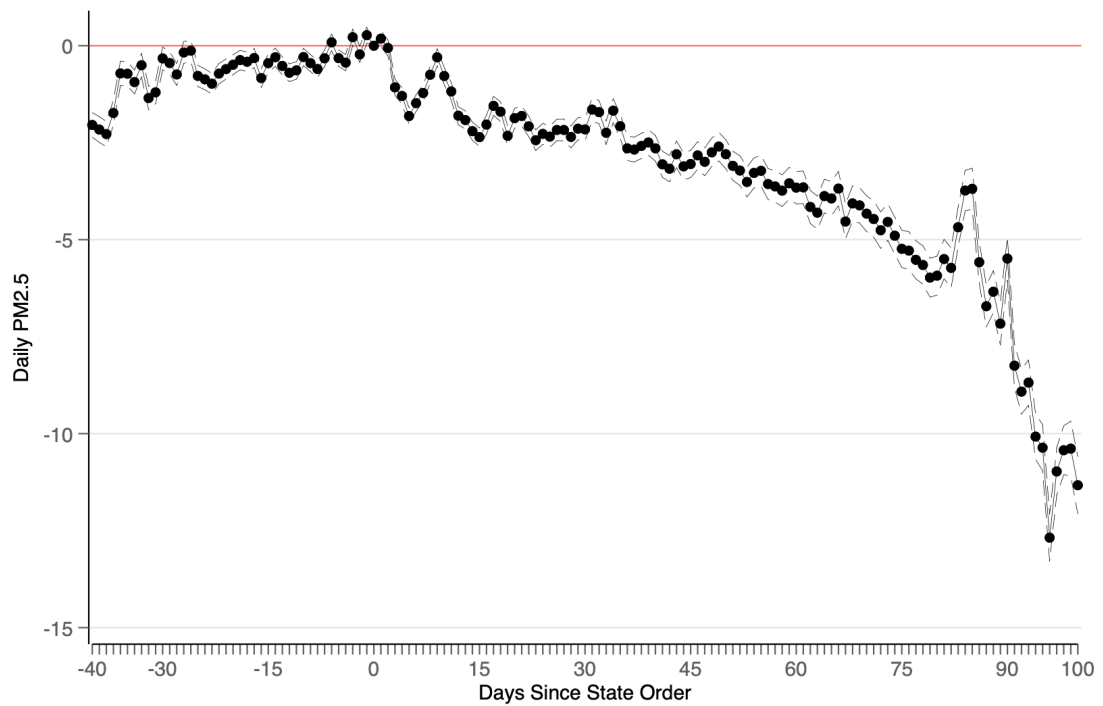
Notes: This map presents counties and states that issued an order prior to April 30, 2020. Counties that issued their own order prior to their state shaded darkest. For states, the darker the fill, the earlier the state issued the order. States in white did not issue an order.

Figure 2: States that Issued a Lockdown



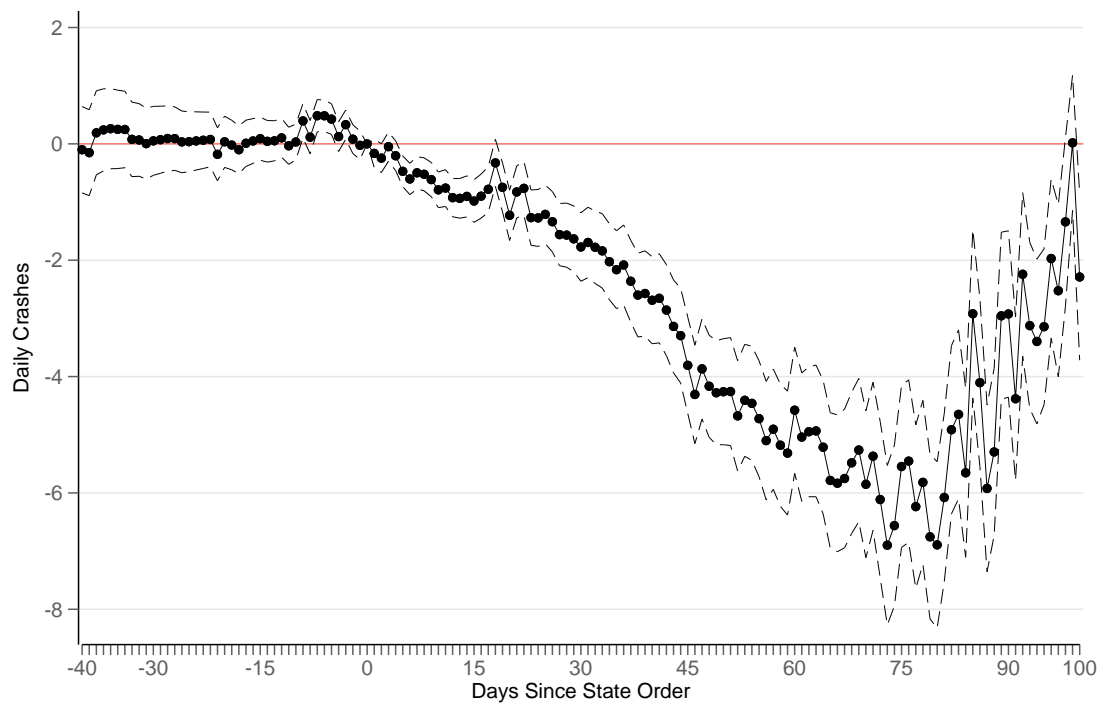
Notes: This map presents states that issued an order prior to April 30, 2020. The darker the fill, the earlier the state issued the order. States in white did not issue an order.

Figure 3: PM2.5 Concentrations Over Time



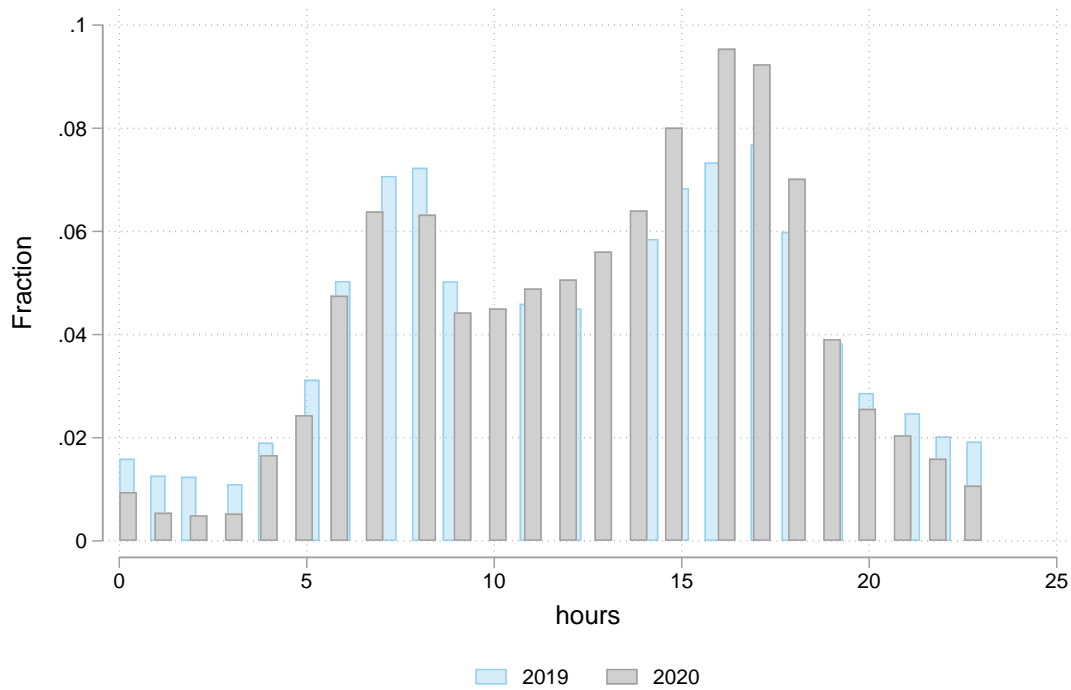
Notes: This figure presents regression coefficients for PM2.5 concentrations corresponding to number of days before/after state order issued. Temperature, precipitation, COVID-19 cases and deaths, and other policy controls are included along with date and county fixed effects. Confidence intervals at 95% presented.

Figure 4: Traffic Collisions Over Time



Notes: This figure presents regression coefficients for collisions corresponding to number of days before/after state order issued. Temperature, precipitation, COVID-19 cases and deaths, and other policy controls are included along with date and county fixed effects. Confidence intervals at 95% presented.

Figure 5: Traffic Collisions Across Hours of Day



Notes: This figure presents histograms for collisions across all hours of the day for our sample period and the corresponding time period in 2019.

Table 1: Summary Statistics

	Mean	Std.Dev.	Max	Min	Count
Pollution					
PM2.5	6.641	3.534	84.4	0.1	200094
PM2.5 (UK)	9.977	8.015	45.0	1.4	25906
PM2.5 (GE)	8.691	6.427	85.4	.7	66407
PM2.5 (SP)	6.984	4.533	34.9	1.0	9648
PM2.5 (FR)	8.238	5.803	189.1	0.5	23880
PM2.5 (IT)	8.594	4.559	70.6	1.4	29487
Collisions					
Collisions	1.770	9.949	811.0	0.0	237408
Severity 1 collisions	0.081	1.095	72.0	0.0	237408
Severity 2 collisions	1.293	8.301	681.0	0.0	237408
Severity 3 collisions	0.334	1.844	116.0	0.0	237408
Severity 4 collisions	0.061	0.537	31.0	0.0	237408
COVID-19					
COVID cases per 10k	5.946	22.448	625.5	0.0	237408
COVID deaths per 10k	0.264	1.262	32.0	0.0	237408
County-days under lockdown	0.364	0.481	1.0	0.0	237408
Day care closure	0.125	0.330	1.0	0.0	237408
Eviction moratorium	0.223	0.416	1.0	0.0	237408
Mandatory face mask in public	0.055	0.229	1.0	0.0	237408
Mandatory quarantine for visitors	0.019	0.138	1.0	0.0	237408

Notes: Authors' calculations. PM2.5 is 24-hour daily concentration of PM2.5 in $\mu\text{g}/\text{m}^3$. Collisions data gathered from [Moosavi et al. \(2019\)](#). The severity of an accident is coded as a number ranging from 1 to 4 with 1 being the smallest impact on traffic and 4 being a significant impact on traffic.

Table 2: State Orders and Pollution (PM2.5)

	(1)	(2)	(3)	(4)	(5)
	PM2.5	PM2.5	PM2.5	PM2.5	PM2.5
During safer-at-home-order	-1.671 (0.454)	-1.673 (0.454)	-1.673 (0.455)	-1.607 (0.496)	-1.372 (0.413)
COVID cases per 10k		-0.003 (0.004)	-0.003 (0.004)	-0.003 (0.004)	-0.002 (0.004)
COVID deaths per 10k			0.003 (0.033)	-0.004 (0.034)	-0.006 (0.035)
Constant	6.704 (0.809)	6.704 (0.808)	6.704 (0.808)	6.709 (0.816)	6.460 (0.801)
County FE	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y
COVID-19 policies				Y	Y
Weather controls					Y
Observations	200094	200094	200094	200094	200094
Counties	1592	1592	1592	1592	1592

Notes: State orders significantly reduce PM2.5. The dependent variable is average daily PM2.5 concentration at the county-level. The time period spans January 1st, 2020 through the moment the statewide safer-at-home ended. COVID-19 known cases and deaths per 10,000 people. Robust standard errors clustered at the state-level reported in parentheses. All columns include county and date fixed effects. Sample restricted to counties within 50km of an air pollution monitoring station.

Table 3: State Orders and Polluted Days

	(1)	(2)	(3)	(4)	(5)
	PM2.5>12	PM2.5>12	PM2.5>12	PM2.5>12	PM2.5>12
During safer-at-home-order	-0.103 (0.032)	-0.103 (0.032)	-0.104 (0.032)	-0.099 (0.035)	-0.089 (0.031)
COVID cases per 10k		-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
COVID deaths per 10k			-0.001 (0.002)	-0.001 (0.002)	-0.002 (0.002)
Constant	0.109 (0.039)	0.109 (0.039)	0.109 (0.039)	0.109 (0.039)	0.093 (0.038)
County FE	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y
COVID-19 policies				Y	Y
Weather controls					Y
Observations	200094	200094	200094	200094	200094
Counties	1592	1592	1592	1592	1592

Notes: State orders significantly reduce polluted days. The dependent variable takes a value of 1 if PM2.5 is above the Annual National Ambient Air Quality Standard of $12 \mu\text{g}/\text{m}^3$. The time period spans January 1st, 2020 through the moment the statewide safer-at-home ended. COVID-19 known cases and deaths per 100 people. Robust standard errors clustered at the state-level reported in parentheses. All columns include county and date fixed effects.

Table 4: European National Orders and Pollution (PM2.5)

	(1)	(2)	(3)	(4)	(5)
	PM2.5	PM2.5	PM2.5	PM2.5	PM2.5
During lockdown	-1.047*** (0.036)	-1.069*** (0.033)	-0.969*** (0.036)	-1.676*** (0.037)	-1.690*** (0.037)
COVID cases per 10k		-0.005*** (0.001)	-0.003** (0.001)	0.003** (0.001)	0.006*** (0.001)
COVID deaths per 10k			-0.117*** (0.015)	-0.015 (0.016)	0.034** (0.016)
Constant	35.373*** (0.135)	24.137*** (0.121)	24.151*** (0.121)	24.254*** (0.119)	24.055*** (0.119)
Date FE	Y	Y	Y	Y	Y
Mask mandate				Y	Y
Quarantine mandate				Y	Y
School closures				Y	Y
Temperature					Y
Precipitation					Y
Observations	155328	138568	138568	138568	136300

Notes: National orders significantly reduce PM2.5 in France, Germany, Italy, Spain and the United Kingdom. The dependent variable is average daily PM2.5 concentration, measured at the population centroid for an administrative area from the three nearest air quality monitors. The mean concentration during the period is 8.7, and the within-unit standard deviation is 6.0. An observation is an area-day. A total of 841 areas are used with 96 from France (departments), 403 from Germany (kreise), 113 from Italy (provinces), 55 from Spain (provinces) and 192 from the United Kingdom (counties). Observations are from the first to the 300th day of 2020, which includes both before, during, and after lockdowns. Standard errors reported in parentheses. All columns include area and date fixed effects.

Table 5: State Orders and Collisions

	(1)	(2)	(3)	(4)	(5)
During safer-at-home-order	0.840 (0.050)	0.839 (0.050)	0.838 (0.050)	0.826 (0.045)	0.793 (0.045)
COVID cases per 10k		1.002 (0.000)	1.003 (0.001)	1.002 (0.001)	1.002 (0.001)
COVID deaths per 10k			0.986 (0.012)	0.981 (0.011)	0.983 (0.011)
County FE	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y
COVID-19 policies				Y	Y
Weather controls					Y
Observations	237569	237569	237569	237569	237408
Counties	1711	1711	1711	1711	1710

Notes: State orders significantly reduce traffic collisions. Poisson model with fixed effects. The dependent variable is count of traffic collisions at the county-level. Coefficients are incidence rate-ratios, wherein a value below one indicates a decrease in the dependent variable and a value above indicates an increase. The time period is January 1st, 2020 through the moment the statewide safer-at-home ended. COVID-19 known cases and deaths per 100 people. Robust standard errors reported in parentheses. All columns include county and date fixed effects.

Table 6: State Orders and Collision Severity

	(1)	(2)	(3)	(4)	(5)
	Any	Severity 1	Severity 2	Severity 3	Severity 4
During safer-at-home-order	0.793 (0.045)	0.855 (0.031)	0.769 (0.034)	1.006 (0.087)	1.179 (0.146)
COVID cases per 10k	.998 (0.001)	0.998 (.001)	1.001 (0.001)	1.004 (0.001)	1.004 (0.001)
COVID deaths per 10k	1.033 (0.011)	1.033 (.0179)	0.969 (0.017)	0.970 (0.012)	1.013 (0.016)
County FE	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y
COVID-19 policies	Y	Y	Y	Y	Y
Weather controls	Y	Y	Y	Y	Y
Observations	237408	60138	207757	166441	145069
Counties	1710	418	1490	1189	1031

Notes: Poisson model with fixed effects. The dependent variable is count of traffic collisions at the county-level. Coefficients are incidence rate-ratios, wherein a value below one indicates a decrease in the dependent variable and a value above indicates an increase. The time period is January 1st, 2020 through the moment the statewide safer-at-home ended. COVID-19 known cases and deaths per 100 people. Robust standard errors reported in parentheses for all columns except column 2, which is non-singular when robust standard errors are applied. All columns include county and date fixed effects.

Table 7: Travel Distance and Collisions – Instrumental Variable

	(1)	(2)	(3)
	All	Urban	Rural
Travel Distance	4.061 (0.999)	9.187 (2.576)	0.071 (0.133)
County FE	Y	Y	Y
Date FE	Y	Y	Y
Case & Death rates	Y	Y	Y
COVID-19 policies	Y	Y	Y
Weather controls	Y	Y	Y
Kleibergen-Papp F-stat	1733	807	755
Observations	159488	159488	228352

Notes: 2SLS with fixed effects. The dependent variable (second stage) is the number of traffic collisions at the county-level. The instrumental variable is the presence of a statewide safer-at-home policy. The time period is March 1st, 2020 through the moment the statewide safer-at-home ended. COVID-19 known cases and deaths per 100 people. Robust standard errors reported in parentheses. All columns include county and date fixed effects.

Appendix: NOT FOR PUBLICATION

7.1 Non-Pharmaceutical Interventions

Day care closure: “The date a state closed daycares statewide. Only included directives/orders. Did not include guidance or recommendations. Order must apply to entire state.”

Face masks: “The date a state mandated face mask use in public spaces by all individuals statewide. The order does not have to apply to all public spaces, but must apply state wide. Only included directives/orders. Did not include guidance or recommendations. Order must apply to entire state.”

Freezes on evictions: “The date a state stopped the initiation of evictions (overall or due to COVID-19 related issues) statewide. This could be mandated from governors or through the state court system. Did not include guidance or recommendations. Order must apply to entire state.”

Quarantine: “The date a state first mandated that individuals arriving in their state from any state must undergo quarantine. Did not include guidance or recommendations. Order must apply to entire state. Quarantine order must apply to visitors using all forms of transportation to enter the state (not just air travel).”

7.2 Simulations Using Synthetic Control Methods: Pollution

7.2.1 Simulations Methodology Here we detail a robustness check for the magnitude of our findings and construct a slightly different comparison group.

In our setting, areas can be one of three groups at any point in time, a) areas that have not *yet* had a state order applied to them b) areas that will *never* have a state order applied to them, or c) areas that currently have a state order applied. In an effort to construct a counterfactual (what would PM2.5 concentrations looked like in areas that currently have a state order applied), we use synthetic control methods to form a weighted convex combination of areas that never have a state order applied for every (eventually) treated area.

The estimates in this paper that use panel fixed effects and within-unit variation of the treatment variable use as a comparison group areas that are not-yet treated. This application of the Synthetic Control Methods (SCM) allows us to bring in information (in the form of a synthetic control area for each treated area) of the PM2.5 evolution that occurs in states during the treatment period. The SCM requires statistical ‘donor’ areas - which we restrict to be areas that are not ever treated - to donate their PM2.5 evolutions to those that are treated. We fit the SCM counterfactual on their pre-safer-at-home order PM2.5 average concentrations.

To construct our synthetic matching, we follow the steps in [Abadie et al. \(2010\)](#).

The idea of this method is to match a treated area (with a state order) to a group of control areas having similar pollution levels prior to the SAH order’s implementation. The hypothesis is that the treated and control counties would have a similar change in pollution if the order had not been implemented.

We construct a synthetic match for each of the treated areas by solving the following optimization problem and finding the optimal vector of weights:

$$\forall i \in \mathbb{N}, \{w_j^{i*}\}_{j \in \mathbb{U}} = \arg \min \{w_j^i\} \sum_i \sum_t \left[Y_{it} - \sum_j w_j^i Y_{jt} \right]^2$$

Subject to

$$\sum_j w_j^i = 1 \text{ and } \forall j \in \mathbb{U}, \forall i \in \mathbb{N}, w_j^i \geq 0,$$

Where Y_{it} is the pollution for county $i \in \mathbb{N}$ on pre-event $t \in \mathbb{T}$. \mathbb{N} being the set of treated areas and \mathbb{T} the set of pre-order dates. w_j^i is the weight given to county $j \in \mathbb{U}$, the set of control areas.

The pollution level for each synthetic area is constructed as:

$$\hat{Y}_{it} = \sum_j w_j^{i*} Y_{jt}$$

The estimates are put together in the same manner as regressions elsewhere in the paper. Each area is equally weighted in the regressions.

7.2.2 Simulation Results The estimates presented in this paper indicate a large reduction in PM2.5 after a state issues a safer-at-home order. As a robustness check, we use simulated counterfactual PM2.5 levels for each county in a state that issued an order using a ‘synthetic’ county constructed using the `synth` package (described in [Abadie et al. \(2011\)](#)). The results of this exercise are presented in Appendix Table [A16](#) while those of a falsification exercise are presented in Appendix Table [A17](#). The structure of the tables is the same as the bulk of those throughout the paper. Inference using simulations with these counterfactuals as we construct them is not explicitly endorsed by [Abadie et al. \(2010\)](#), so we take these results as a robustness exercise, which provide reassurance that our results are, at the very least, not simply a statistical artifact. For this reason, we remain silent on the statistical significance of these estimates but provide them for the curious reader.

In Appendix Table [A16](#), the dependent variable is the difference between the observed PM2.5 levels and those of the counterfactual. The difference is structured so that a negative value represents a lower observed PM2.5 concentration than expected from the counterfactual. To create the counterfactual, we applied the

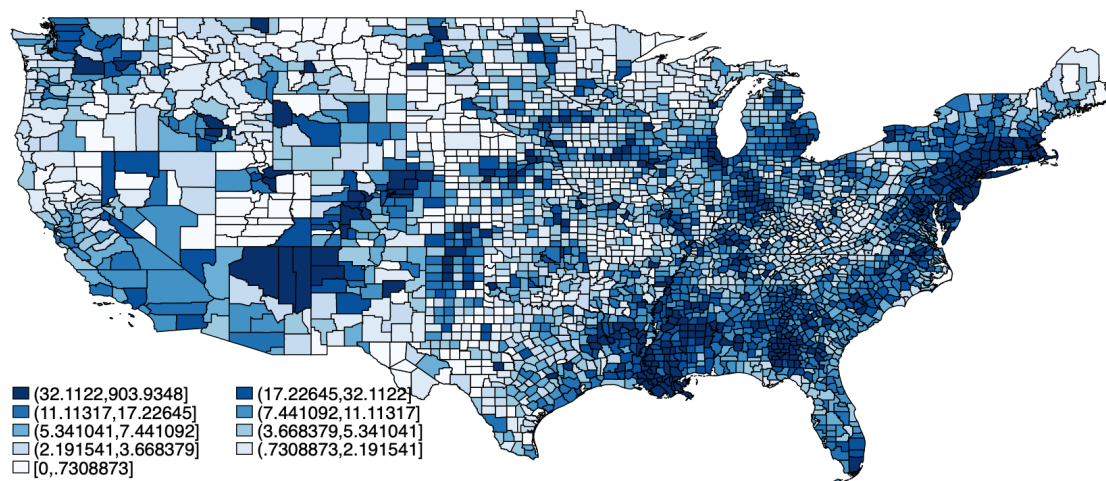
synthetic control method separately for each treated county, allowing for different donor (untreated) county weights to be applied to treated counties as diverse as those from New York or from Texas. The treated sample is necessarily restricted to 1418 counties in the 41 states that issued a safer-at-home order during 2020.

During a safer-at-home order, we see a reduction of around $1 \mu\text{g}/\text{m}^3$ in PM2.5 concentration, which is reassuringly close to the estimates presented in Table 2. The estimates of the reduction are also relatively undisturbed with the introduction of controls including COVID-19 policies (such as mandatory mask usage) and weather.

In Appendix Table A17, we conduct a placebo-in-space exercise, much in the spirit of those introduced in Abadie et al. (2010). The dependent variable is the difference between the observed PM2.5 levels of counties in states that did not issue a safer-at-home order in 2020 and those of a counterfactual constructed from counties in the 8 untreated states. To create the counterfactual, we applied the synthetic control method separately for each untreated county, allowing for different donor (untreated) county weights to be applied to the current untreated county. The sample is necessarily restricted to counties in the 8 states that issue a safer-at-home order during 2020. Reassuringly, this placebo exercise (which assigns a safer-at-home order when one never occurred) exhibits different behaviour than our simulation. The sign of the estimates even flips between specifications, with the inclusion of weather controls. The standard errors are significantly larger, and calculated in the same manner as in the simulation.

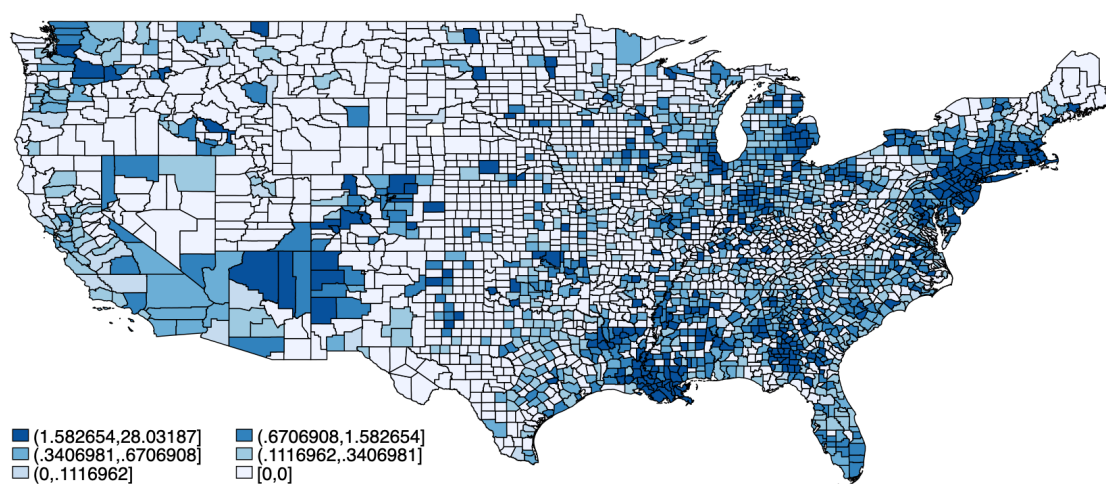
We also provide the same graphical evidence of the leads and lags for this and the placebo exercise. In Appendix Figure A9, we present the difference between observed and counterfactual PM2.5 levels from 40 days before to 100 days after a state order was issued. The results are similar to those presented in Figure 3. In contrast, the estimates for the placebo exercise presented in Figure A10 are much smaller and exhibit a flat trajectory before and after the placebo order's issuance.

Figure A1: COVID-19 Confirmed Cases per 10,000 by County



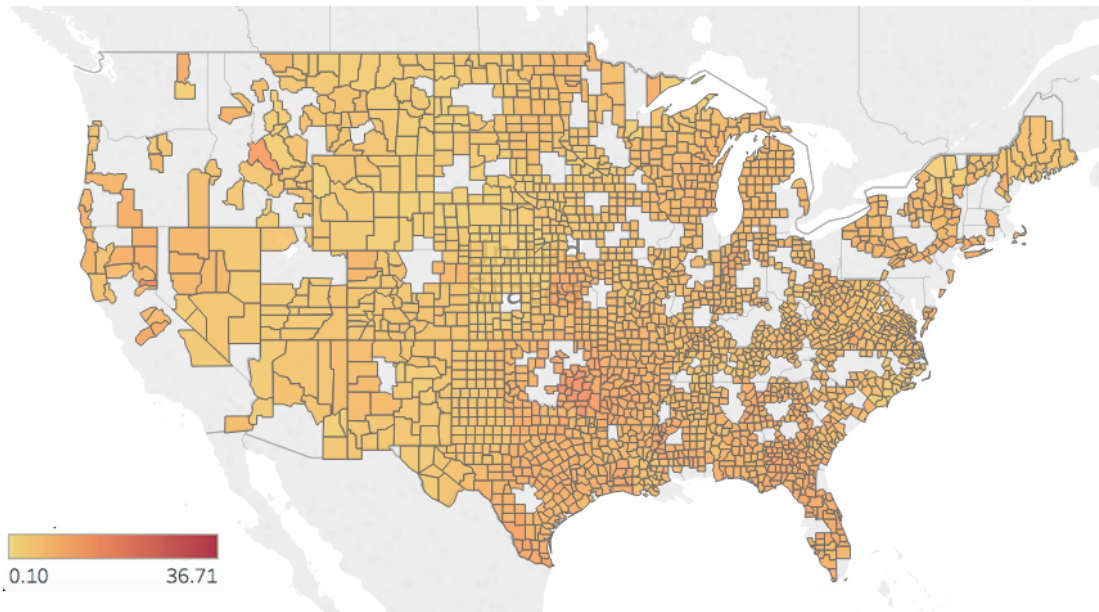
Notes: The map illustrates the cumulative number of (confirmed) COVID-19 cases per 10,000 inhabitants for each county as of May 1, 2020.

Figure A2: COVID-19 Deaths per 10,000 by County



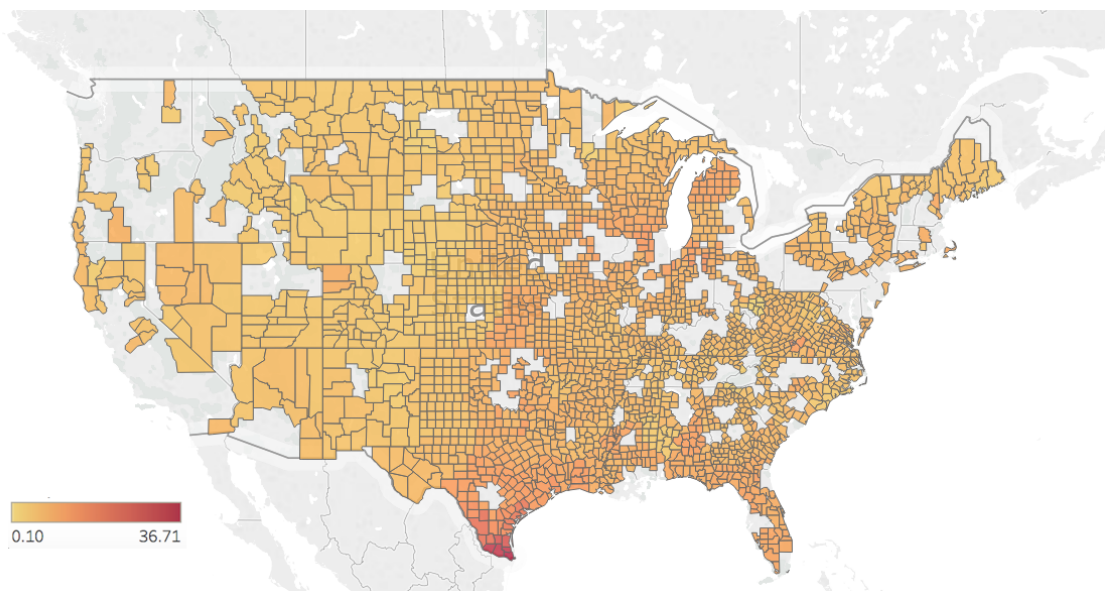
Notes: The map illustrates the number of COVID-19 deaths per 10,000 inhabitants for each county as of May 1, 2020.

Figure A3: Weekly Average PM2.5 Concentrations March 1-7, 2020



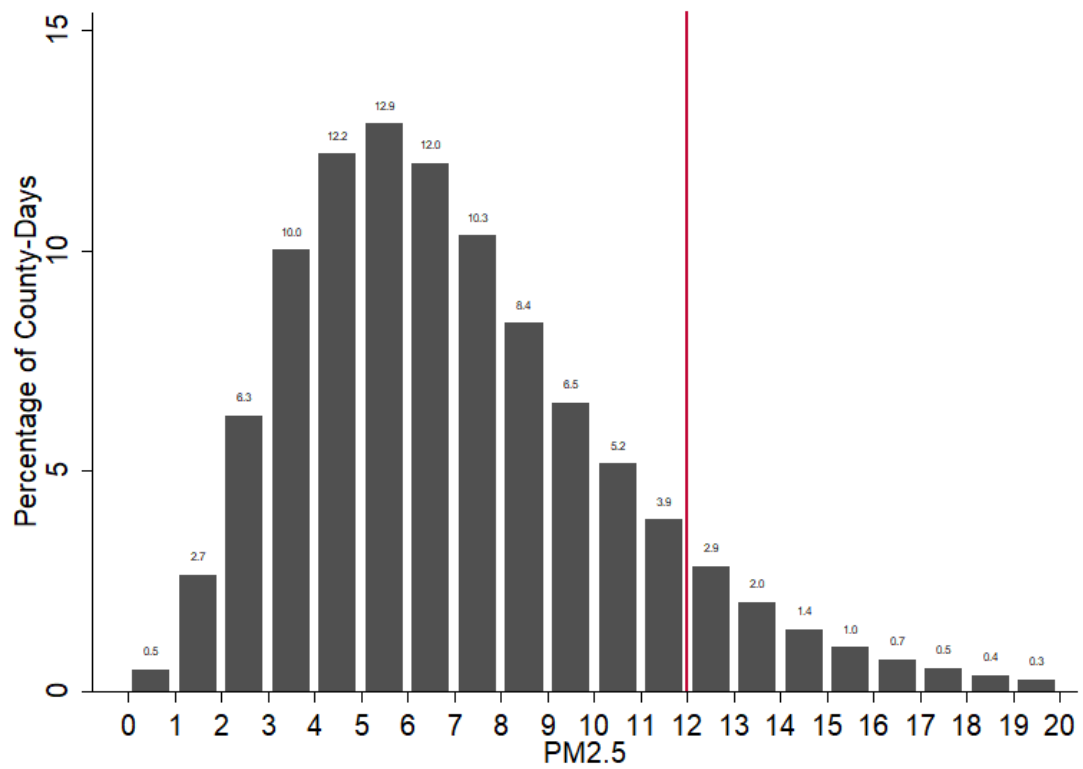
Notes: This map presents PM2.5 concentrations for a baseline week of March 1-7. PM2.5 measures for counties with a population weighted centroid within 50km of an air quality monitoring station.

Figure A4: Weekly Average PM2.5 Concentrations April 19-25, 2020



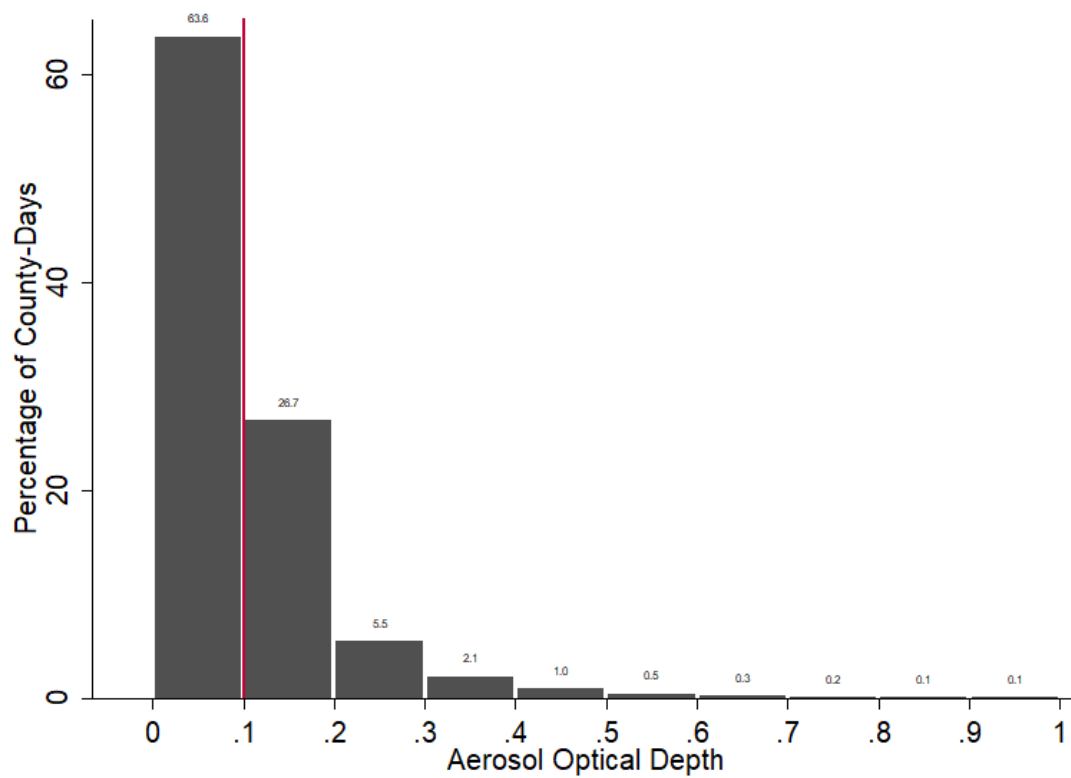
Notes: This map presents PM2.5 concentrations for near end of April 2020. PM2.5 measures for counties with a population weighted centroid within 50km of an air quality monitoring station.

Figure A5: Distribution of PM2.5 Concentrations



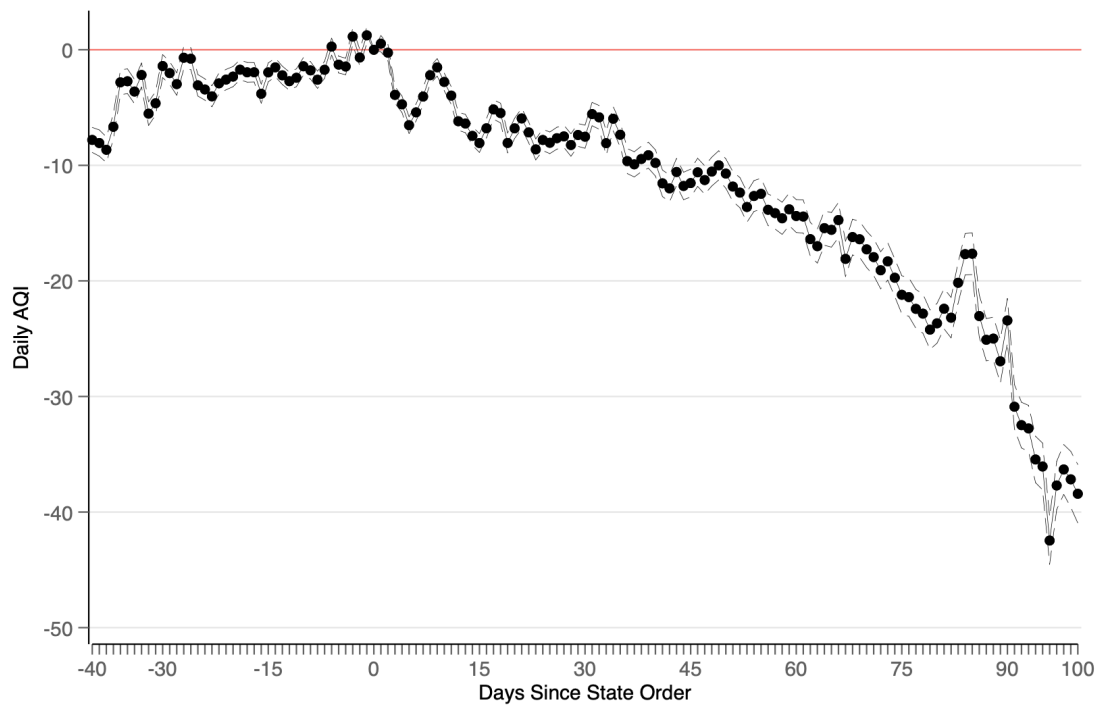
Notes: This figure illustrates the distribution of our dependent variable PM2.5 Concentrations for all county-days in our sample, i.e., all observations.

Figure A6: Distribution of Aerosol Optical Depth



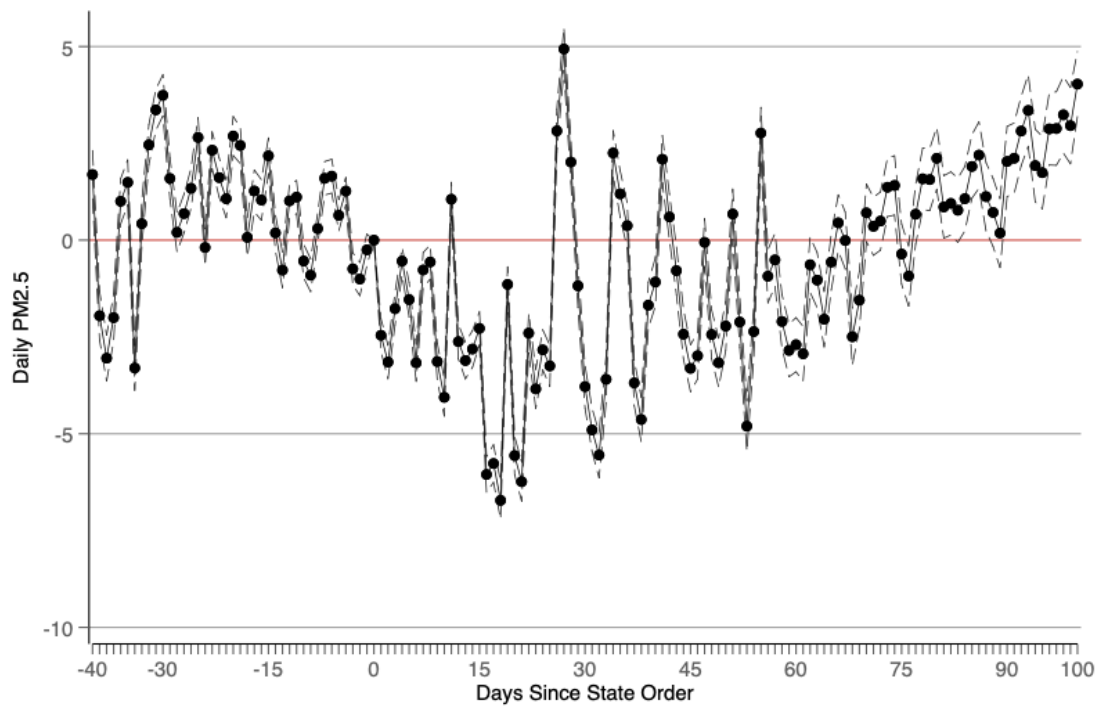
Notes: This figure illustrates the distribution of our dependent variable aerosol optical depth for all county-days in our sample, i.e., all observations.

Figure A7: Air Quality Index (AQI) Over Time



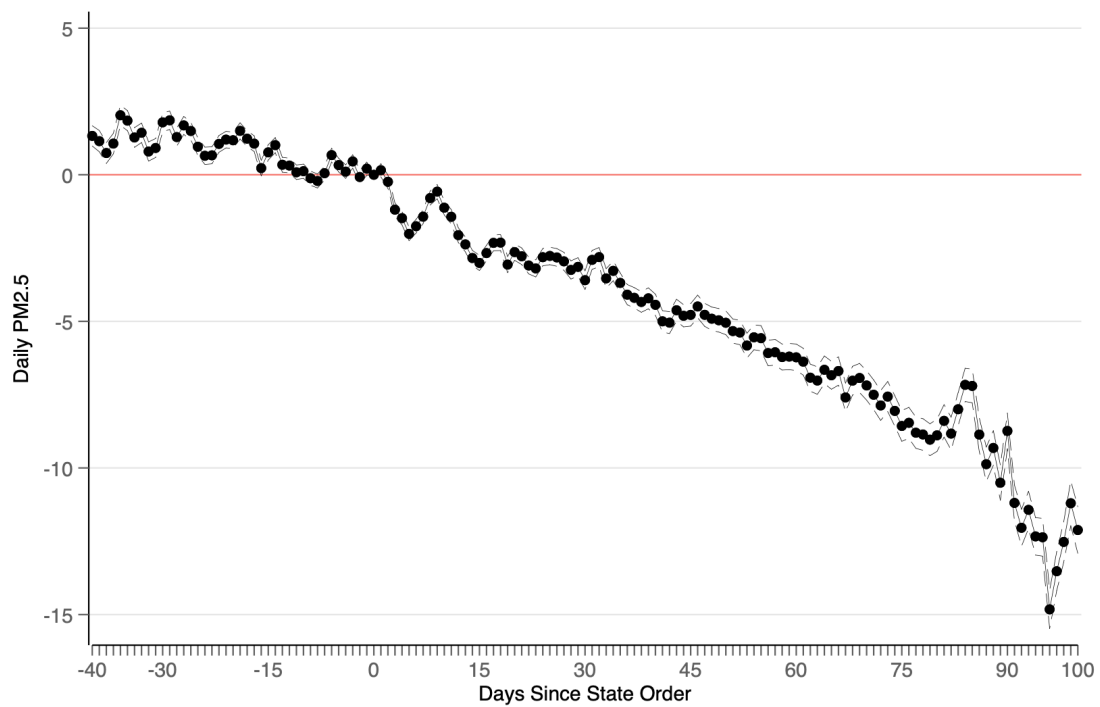
Notes: This figure presents regression coefficients for Air Quality Index (AQI) corresponding to number of days before/after state order issued. Date and county fixed effects included. We also include our full set of weather and policy controls. The lockdown date is presented with a red line. Confidence intervals at 95% presented.

Figure A8: PM2.5 Concentrations Over Time (Europe)



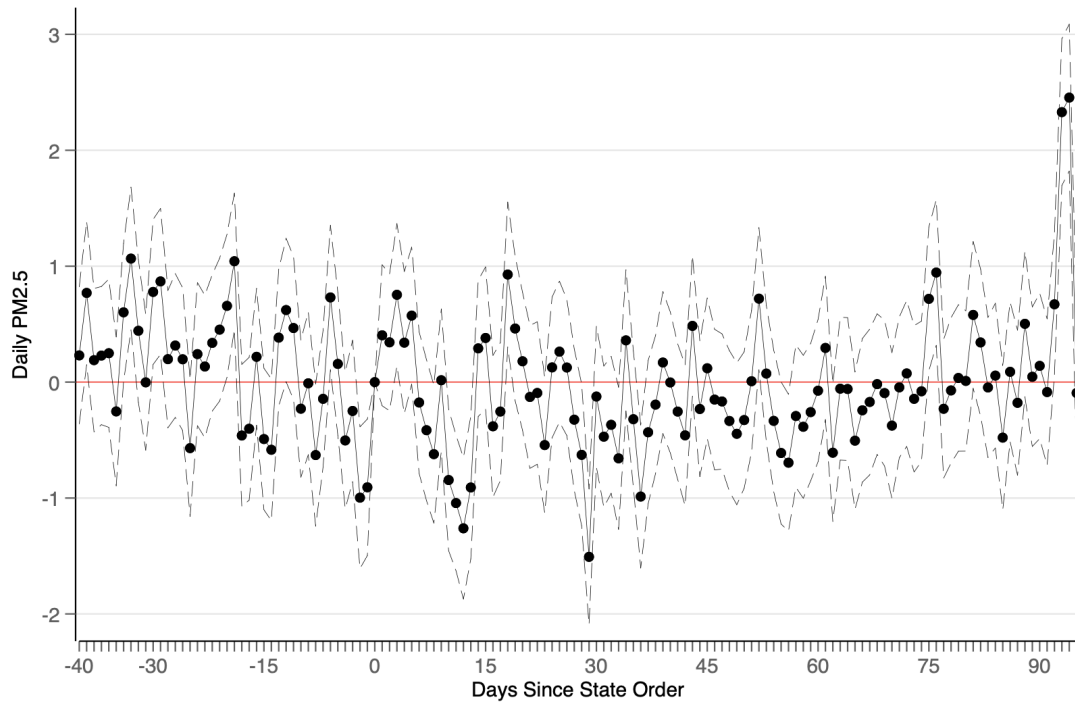
Notes: This figure presents regression coefficients for PM2.5 concentrations corresponding to number of days before/after national order issued. Area and date fixed effects included. We also include our full set of weather and policy controls. The baseline date is presented with a red line. Confidence intervals at 95% presented.

Figure A9: PM2.5 Concentrations Over Time - Synthetic Control



Notes: This figure presents the evolution of the difference between observed and the (simulated) counterfactual levels of PM2.5 expected from a synthetic control for each treated county, before and after state orders. Plotted are regression coefficients of days since state order issued. Significance bands at the 95% level. County fixed effects model. Date fixed effects also included.

Figure A10: PM2.5 Concentrations Over Time - Synthetic Placebo



Notes: The dependent variable is the difference between the observed PM2.5 levels of counties in states that did not issue a safer-at-home order in 2020 and those of a counterfactual county constructed from the remaining counties in the 8 untreated states. Plotted are regression coefficients of days since state order issued. Significance bands at the 95% level. County fixed effects model. Date fixed effects also included.

Table A1: State Orders and Pollution: State-Level

	(1)	(2)	(3)	(4)	(5)
	PM2.5	PM2.5	PM2.5	PM2.5	PM2.5
During safer-at-home-order	-1.476 (0.439)	-1.491 (0.440)	-1.486 (0.438)	-1.429 (0.458)	-1.152 (0.371)
COVID cases per 10k		-0.005 (0.004)	-0.008 (0.012)	-0.005 (0.015)	0.006 (0.015)
COVID deaths per 10k			0.039 (0.135)	-0.031 (0.165)	-0.153 (0.164)
Constant	6.513 (0.833)	6.513 (0.834)	6.513 (0.834)	6.517 (0.838)	6.367 (0.868)
State FE	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y
COVID-19 policies				Y	Y
Weather controls					Y
Observations	5713	5713	5713	5713	5713
Counties	41	41	41	41	41

Notes: State orders significantly reduce PM2.5. The dependent variable is average daily PM2.5 concentration at the state-level. The time period is January 1st, 2020 through the moment the statewide safer-at-home ended. COVID-19 known cases and deaths per 10,000 people. Robust standard errors reported in parentheses. All columns include state and date fixed effects.

Table A2: State Orders and Pollution (PM2.5): Proactive and Reactive Counties

	All		Proactive		Reactive	
	(1)	(2)	(3)	(4)	(5)	(6)
During state order	-1.440 (0.372)	-1.372 (0.413)	-1.729 (0.455)	-1.170 (0.609)	-1.367 (0.398)	-1.286 (0.420)
During county order			-0.501 (0.287)	-0.447 (0.302)		
COVID cases per 10k		-0.002 (0.004)		-0.013 (0.004)		-0.002 (0.004)
COVID deaths per 10k		-0.006 (0.035)		-0.421 (0.427)		-0.008 (0.034)
Constant	6.451 (0.790)	6.460 (0.801)	10.623 (2.574)	10.737 (2.728)	6.078 (0.675)	6.083 (0.681)
Date FE	Y	Y	Y	Y	Y	Y
COVID-19 policies		Y		Y		Y
Weather controls	Y	Y	Y	Y	Y	Y
Observations	200094	200094	15220	15220	184874	184874
Counties	1592	1592	118	118	1474	1474

Notes: The dependent variable is average daily PM2.5 concentration at the county-level. Proactive counties implemented their own orders. Reactive counties had only state orders issued. The time period is January 1st, 2020 through the moment the statewide safer-at-home ended. COVID-19 known cases and deaths per 10,000 people. Robust standard errors clustered at the state-level reported in parentheses. All columns include county and date fixed effects. Sample restricted to counties within 50km of an air pollution monitoring station.

Table A3: State Orders and Pollution (PM2.5): Weighted Estimates

	(1)	(2)	(3)	(4)	(5)
	PM2.5	PM2.5	PM2.5	PM2.5	PM2.5
During safer-at-home-order	-2.522	-2.534	-2.549	-2.567	-2.069
	(0.681)	(0.663)	(0.660)	(0.638)	(0.453)
COVID cases per 10k		-0.008	-0.001	-0.001	0.001
		(0.004)	(0.007)	(0.008)	(0.008)
COVID deaths per 10k			-0.109	-0.126	-0.142
			(0.062)	(0.069)	(0.077)
Constant	11.200	11.199	11.199	11.215	10.394
	(2.013)	(2.024)	(2.024)	(2.027)	(1.980)
County FE	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y
COVID-19 policies				Y	Y
Weather controls					Y
Observations	200094	200094	200094	200094	200094
Counties	1592	1592	1592	1592	1592

Notes: State orders significantly reduce PM2.5, weighted by county population. The dependent variable is average daily PM2.5 concentration at the county-level. The time period spans January 1st, 2020 through the moment the statewide safer-at-home ended. COVID-19 known cases and deaths per 100 people. Standard errors clustered at the state-level reported in parentheses, clustered at the state-level. All columns include county and date fixed effects.

Table A4: State Orders and Air Quality Index

	(1)	(2)	(3)	(4)	(5)
	AQI	AQI	AQI	AQI	AQI
During safer-at-home-order	-6.240	-6.251	-6.251	-6.003	-5.093
	(0.307)	(0.308)	(0.308)	(0.326)	(0.288)
COVID cases per 10k		-0.012	-0.012	-0.013	-0.008
		(0.005)	(0.008)	(0.008)	(0.008)
COVID deaths per 10k			-0.000	-0.022	-0.034
			(0.100)	(0.107)	(0.105)
Constant	25.591	25.591	25.591	25.611	24.695
	(0.436)	(0.436)	(0.436)	(0.438)	(0.438)
County FE	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y
COVID-19 policies				Y	Y
Weather controls					Y
Observations	200094	200094	200094	200094	200094
Counties	1592	1592	1592	1592	1592

Notes: State orders significantly reduce Air Quality Index. The dependent variable is average daily AQI. The time period spans January 1st, 2020 through the moment the statewide safer-at-home ended. COVID-19 known cases and deaths per 10,000 people. Robust standard errors clustered at the state-level reported in parentheses. All columns include county and date fixed effects.

Table A5: State Orders and Air Quality Risk

	(1)	(2)	(3)	(4)	(5)
	AQI>50	AQI>50	AQI>50	AQI>50	AQI>50
During safer-at-home-order	-0.098 (0.031)	-0.098 (0.031)	-0.098 (0.031)	-0.093 (0.033)	-0.084 (0.030)
COVID cases per 10k		-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
COVID deaths per 10k			-0.001 (0.002)	-0.002 (0.002)	-0.002 (0.002)
Constant	0.097 (0.036)	0.097 (0.036)	0.097 (0.036)	0.097 (0.037)	0.082 (0.036)
County FE	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y
COVID-19 policies				Y	Y
Weather controls					Y
Observations	200094	200094	200094	200094	200094
Counties	1592	1592	1592	1592	1592

Notes: State orders significantly reduce Air Quality Risk of being in ‘code yellow’ or above. The dependent variable indicates if average daily AQI exceeds 50, the threshold for moderate health effects from air pollution. The time period spans January 1st, 2020 through the moment the statewide safer-at-home ended. COVID-19 known cases and deaths per 10,000 people. Robust standard errors clustered at the state-level reported in parentheses. All columns include county and date fixed effects.

Table A6: State Orders and Aerosol Optical Depth (Restricted)

	(1)	(2)	(3)	(4)	(5)
	AOD	AOD	AOD	AOD	AOD
During safer-at-home-order	-2.065 (6.909)	-2.055 (6.904)	-2.165 (6.905)	-1.510 (6.365)	1.092 (5.233)
COVID cases per 10k		0.019 (0.043)	0.094 (0.070)	0.082 (0.070)	0.091 (0.066)
COVID deaths per 10k			-1.448 (0.946)	-1.717 (0.964)	-1.775 (0.938)
Constant	38.944 (5.181)	38.937 (5.171)	38.965 (5.170)	38.897 (5.158)	18.538 (6.173)
County FE	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y
COVID-19 policies				Y	Y
Weather controls					Y
Observations	41697	41697	41697	41697	41697
Counties	1541	1541	1541	1541	1541

Notes: State orders reduce aerosol optical depth. The dependent variable is aerosol optical depth. The time period spans January 1st, 2020 through the moment the statewide safer-at-home ended. COVID-19 known cases and deaths per 10,000 people. Robust standard errors clustered at the state-level reported in parentheses. All columns include county and date fixed effects. The sample is restricted to counties within 50km of a monitoring station.

Table A7: State Orders and Aerosol Optical Depth (All)

	(1)	(2)	(3)	(4)	(5)
	AOD	AOD	AOD	AOD	AOD
During safer-at-home-order	-2.832	-2.823	-2.852	-2.328	-0.541
	(5.276)	(5.273)	(5.277)	(5.103)	(4.264)
COVID cases per 10k		0.025	0.056	0.051	0.054
		(0.033)	(0.052)	(0.050)	(0.047)
COVID deaths per 10k			-0.717	-0.873	-0.804
			(0.778)	(0.765)	(0.745)
Constant	35.593	35.585	35.596	35.473	16.872
	(5.485)	(5.479)	(5.478)	(5.492)	(7.376)
County FE	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y
COVID-19 policies				Y	Y
Weather controls					Y
Observations	77279	77279	77279	77279	77279
Counties	2532	2532	2532	2532	2532

Notes: State orders significantly reduce aerosol optical depth. The dependent variable is aerosol optical depth. The time period spans January 1st, 2020 through the moment the statewide safer-at-home ended. COVID-19 known cases and deaths per 10,000 people. Robust standard errors clustered at the state-level reported in parentheses. All columns include county and date fixed effects.

Table A8: State Orders and Pollution (PM2.5) Alternative Estimators

	(1)	(2)	(3)	(4)
	Baseline	Simple Average	Dynamic Average	Group Average
During safer-at-home-order	-1.671	-1.027	-0.749	-0.449
	(0.084)	(0.157)	(0.164)	(0.144)
County FE	Y	Y	Y	Y
Date FE	Y	Y	Y	Y
Observations	200094	200094	200094	200094
Counties	1592	1592	1592	1592

Notes: State orders significantly reduce PM2.5. The dependent variable is average daily PM2.5 concentration at the county-level. Column 1 contains the baseline estimate. Columns 2–4 provide alternative estimators based on [Callaway and Sant’Anna \(Forthcoming\)](#): the “simple” aggregated average treatment on the treated (ATT), the “dynamic” aggregated ATT, and the “group” aggregated ATT, respectively. The time period spans January 1st, 2020 through the moment the statewide safer-at-home ended. Robust standard errors clustered at the state-level reported in parentheses. All columns include county and date fixed effects. Sample restricted to counties within 50km of an air pollution monitoring station.

Table A9: Stringency of State Orders

	PM2.5		Collisions	
	(1)	(2)	(3)	(4)
Less Stringent Order	-0.194 (0.714)	-0.110 (0.592)	0.899 (0.008)	0.872 (0.008)
More Stringent Order	-0.903 (0.656)	-0.778 (0.539)	0.937 (0.009)	0.897 (0.008)
COVID-19 Cases	-0.003 (0.004)	-0.002 (0.004)	1.002 (0.000)	1.002 (0.000)
COVID-19 Deaths	0.002 (0.034)	-0.003 (0.034)	0.985 (0.002)	0.987 (0.002)
Constant	6.693 (0.163)	6.462 (0.163)		
County FE	Y	Y	Y	Y
Date FE	Y	Y	Y	Y
COVID-19 policies	Y	Y	Y	Y
Weather controls		Y		Y
Observations	190370	190370	270875	270714
Counties	1592	1592	1894	1893

Notes: The dependent variable is average daily PM2.5 concentration at the county-level for columns 1 and 2 and count of traffic collisions at the county-level for columns 3 and 4, respectively. The time period spans January 1st, 2020 through the moment the statewide safer-at-home ended. COVID-19 known cases and deaths per 10,000 people. Robust standard errors clustered at the state-level reported in parentheses for columns 1 and 2. Robust standard errors reported in parentheses for columns 3 and 4. All columns include county and date fixed effects.

Table A10: State Orders and Pollution Heterogeneity (PM2.5)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Urban	Rural	Majority Trump	Minority Trump	Above Median 65+	Below Median 65+	Above Median Work from Home	Below Median Work from Home
During order	-1.484 (0.463)	-1.200 (0.371)	-1.159 (0.404)	-1.762 (0.408)	-0.945 (0.451)	-1.629 (0.433)	-1.403 (0.572)	-1.282 (0.485)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
COVID-19 policies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	109333	90761	142946	57148	75769	124325	110433	89661
Counties	816	776	1169	423	637	955	849	743

Notes: The dependent variable is average daily PM2.5 concentration at the county-level. The time period is January 1st, 2020 through the moment the statewide safer-at-home ended. COVID-19 known cases and deaths per 10,000 people. Robust standard errors clustered at the state-level reported in parentheses. All columns include date fixed effects. Sample restricted to counties within 50km of an air pollution monitoring station. Columns 1–2 are the effects of the order for urban and rural counties, respectively. Columns 2–4 are for counties in which a majority voters voted for President Trump. Columns 5–6 are for counties with with an above and below median share of population aged 65 and over, respectively. Columns 7–8 are for counties in states with above and below median shares of occupations that can be done remotely, respectively.

Table A11: Characteristics of Trump and non-Trump Majority Counties (Pre-Order Time Period)

Variable	(1) Non-Trump		(2) Trump		T-test Difference (1)-(2)
	N	Mean/SD	N	Mean/SD	
PM2.5	23063	6.649 (3.602)	131957	6.398 (3.679)	0.250
PM2.5 > 12	23063	0.082 (0.274)	131957	0.065 (0.247)	0.016
Travel distance	22669	-0.118 (0.195)	127003	-0.106 (0.180)	-0.011
Urban County	23101	0.700 (0.458)	132433	0.307 (0.461)	0.392
Above median population 65+	23101	0.254 (0.435)	132433	0.582 (0.493)	-0.328
Above median work from home	23101	0.564 (0.496)	132433	0.410 (0.492)	0.154
COVID cases per 10k	23101	5.759 (30.020)	132433	6.829 (37.699)	-1.070
COVID deaths per 10k	23101	0.087 (0.435)	132433	0.131 (0.784)	-0.044

Notes: The value displayed for t-tests are the differences in the means across the groups.

Table A12: European National Orders and Pollution (PM2.5) By Country

	(1) FR	(2) GE	(3) IT	(4) SP	(5) UK
During lockdown	-14.649 (0.592)	-44.275 (0.221)	-4.128 (0.572)	-15.736 (0.367)	-21.861 (0.379)
Constant	22.406 (0.416)	48.193 (0.094)	15.604 (0.279)	17.531 (0.263)	27.071 (0.159)
Date FE	Y	Y	Y	Y	Y
Temperature	Y	Y	Y	Y	Y
Precipitation	Y	Y	Y	Y	Y
Observations	23880	66276	28432	9010	25188

Notes: National orders significantly reduce PM2.5 in France, Germany, Italy, Spain and the United Kingdom. The dependent variable is average daily PM2.5 concentration, measured at the population centroid for an administrative area from the three nearest air quality monitors. The mean concentration during the period is 8.7, and the within-unit standard deviation is 6.0. An observation is an area-day. A total of 841 areas are used with 96 from France (departments), 403 from Germany (kreise), 113 from Italy (provinces), 55 from Spain (provinces) and 192 from the United Kingdom (counties). Observations are from the first to the 300th day of 2020, which includes both before, during, and after lockdowns. Standard errors reported in parentheses. All columns include area and date fixed effects.

Table A13: State Orders and Collisions: State-Level

	(1)	(2)	(3)	(4)	(5)
During safer-at-home-order	0.840 (0.109)	0.839 (0.114)	0.834 (0.110)	0.823 (0.095)	0.797 (0.092)
COVID cases per 10k		1.003 (0.001)	1.010 (0.004)	1.009 (0.003)	1.008 (0.003)
COVID deaths per 10k			0.908 (0.034)	0.919 (0.029)	0.930 (0.029)
State FE	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y
COVID-19 policies				Y	Y
Weather controls					Y
Observations	5716	5716	5716	5716	5716
Counties	41	41	41	41	41

Notes: State orders significantly reduce traffic collisions. Poisson model with fixed effects. The dependent variable is count of traffic collisions at the state-level. Coefficients are incidence rate-ratios, wherein a value below one indicates a decrease in the dependent variable and a value above indicates an increase. The time period is January 1st, 2020 through the moment the statewide safer-at-home ended. COVID-19 known cases and deaths per 10,000 people. Robust standard errors reported in parentheses. All columns include state and date fixed effects.

Table A14: State Orders and Collisions: Proactive and Reactive Counties

	All		Proactive		Reactive	
	(1)	(2)	(3)	(4)	(5)	(6)
During order	0.806 (0.049)	0.793 (0.045)	0.752 (0.086)	0.750 (0.067)	0.865 (0.053)	0.850 (0.054)
During county order			0.762 (0.057)	0.756 (0.048)		
COVID cases per 10k		1.002 (0.001)		1.007 (0.005)		1.002 (0.001)
COVID deaths per 10k		0.983 (0.011)		0.809 (0.098)		0.979 (0.010)
County FE	Y	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y	Y
COVID-19 policies		Y		Y		Y
Weather controls	Y	Y	Y	Y	Y	Y
Observations	237408	237408	16479	16479	220929	220929
Counties	1710	1710	121	121	1589	1589

Notes: The dependent variable is average daily collisions at the county-level. Proactive counties implemented their own orders. Reactive counties had only state orders issued. The time period is January 1st, 2020 through the moment the statewide safer-at-home ended. COVID-19 known cases and deaths per 10,000 people. Robust standard errors reported in parentheses. All columns include county and date fixed effects.

Table A15: State Orders and Collision Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Urban	Rural	Majority Trump	Minority Trump	Above Median 65+	Below Median 65+	Above Median Work from Home	Below Median Work from Home
During order	0.774 (0.046)	1.077 (0.099)	0.881 (0.051)	0.745 (0.053)	0.776 (0.060)	0.804 (0.047)	0.706 (0.049)	1.085 (0.102)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
COVID-19 policies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124770	112638	171226	66182	98950	138458	142019	95389
Counties	889	821	1247	463	704	1006	1004	706

Notes: The dependent variable is count of traffic collisions at the county-level. Coefficients are incidence rate-ratios, wherein a value below one indicates a decrease in the dependent variable and a value above indicates an increase. The time period is January 1st, 2020 through the moment the statewide safer-at-home ended. COVID-19 known cases and deaths per 10,000 people. Robust standard errors reported in parentheses. All columns include county and date fixed effects. Columns 1–2 are the effects of the order for urban and rural counties, respectively. Columns 3–4 are for counties in which a majority voters voted for President Trump. Columns 5–6 are for counties with an above and below median share of population aged 65 and over, respectively. Columns 7–8 are for counties in states with above and below median shares of occupations that can be done remotely, respectively.

Table A16: State Orders and Pollution (PM2.5): Simulation Using Synthetic Control

	(1)	(2)	(3)	(4)	(5)
	synth_diff	synth_diff	synth_diff	synth_diff	synth_diff
During order	-1.060	-1.057	-1.059	-1.072	-0.884
	(0.397)	(0.397)	(0.397)	(0.419)	(0.339)
COVID cases per 10k		0.002	0.002	0.002	0.002
		(0.001)	(0.001)	(0.001)	(0.001)
COVID deaths per 10k			-0.009	-0.002	0.003
			(0.030)	(0.027)	(0.031)
Constant	1.045	1.044	1.044	1.044	0.757
	(0.866)	(0.866)	(0.866)	(0.869)	(0.851)
County FE	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y
COVID-19 policies				Y	Y
Weather controls					Y
Observations	237243	237243	237243	237243	237243
Counties	1418	1418	1418	1418	1418

Notes: State orders significantly reduce PM2.5. The dependent variable is the *difference* between observed and counterfactual PM2.5 at the county-day level. For each county that issued a lockdown order, a synthetic counterfactual county was created from a weighted convex combination of counties from the 8 ‘donor’ states that did not issue an order. Synthetic weights determined by pre-treatment period PM2.5 levels. The time period is January 1st, 2020 through June 30th, 2020. COVID-19 known cases and deaths per 10,000 people using 2019 population estimates. Standard errors reported in parentheses, clustered at the state-level. All columns include state and date fixed effects. Sample restricted to counties within 50km of an air pollution monitoring station.

Table A17: State Orders and Pollution (PM2.5): Simulation Using Synthetic Control Placebo

	(1)	(2)	(3)	(4)	(5)
During order (placebo)	-0.705 (0.962)	-0.694 (0.966)	-0.694 (0.965)	-0.720 (0.978)	1.084 (2.237)
COVID cases per 10k		-0.002 (0.002)	-0.003 (0.002)	-0.003 (0.002)	-0.003 (0.002)
COVID deaths per 10k			0.052 (0.066)	0.055 (0.065)	0.066 (0.064)
Constant	0.301 (0.942)	0.301 (0.945)	0.300 (0.944)	0.300 (0.934)	0.369 (0.940)
County FE	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y
COVID-19 policies				Y	Y
Weather controls					Y
Observations	30989	30989	30989	30989	30989
Counties	209	209	209	209	209

Notes: Placebo state orders do not significantly affect PM2.5. The dependent variable is the *difference* between observed and counterfactual PM2.5 at the county-day level. For each county in each of the 8 states that did not issue a lockdown order, a synthetic counterfactual county was created from a weighted convex combination of remaining counties in the 8 ‘donor’ states that did not issue an order. Synthetic weights determined by pre-treatment period PM2.5 levels. The time period is January 1st, 2020 through June 30th, 2020. COVID-19 known cases and deaths per 10,000 people using 2019 population estimates. Standard errors reported in parentheses, clustered at the state-level. All columns include state and date fixed effects. Sample restricted to counties within 50km of an air pollution monitoring station.