I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 13255

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

Abel Brodeur
Nikolai Cook
Taylor Wright

MAY 2020

I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 13255

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

Abel Brodeur
University of Ottawa and IZA

Nikolai Cook
University of Ottawa

Taylor Wright
University of Ottawa

MAY 2020

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

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

In response to COVID-19, dramatic safer-at-home policies were implemented. The understanding of their impacts on social distancing, travel and pollution is in its infancy. We pair a differences-in-differences framework and synthetic control methods with rich cellular tracking and high frequency air pollution data. We find that state and U.S. county safer-at-home policies are successful in encouraging social distance; beginning the day of the policy trips outside the home are sharply decreased while time in residence rises sharply. With less vehicle traffic, we find: a 50% reduction in vehicular collisions; an approximately 25% reduction in Particulate Matter (PM2.5) concentrations; and a reduction of the incidence of county-days with an air quality index of code yellow or above by two-thirds. We calculate that the benefits from avoided car collisions could range from \$7 billion to \$24 billion while the benefits from reduced pollution could range from \$650 million to \$13.8 billion.

JEL Classification: P48, Q53, Q58

Keywords: COVID-19, safer-at-home, lockdowns, pollution, traffic, car crashes

Corresponding author:
Abel Brodeur
Social Sciences Building
University of Ottawa
120 University
Ottawa, ON K1N 6N5
Canada

E-mail: abrodeur@uottawa.ca

* We thank Mohammad Elfeitori and Ramanvir Grewal for their excellent research assistance.

The emergence of COVID-19 (formally SARS-CoV-2 by the International Committee of 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 impacts. This pandemic has caused governments worldwide to implement curfews and safer-at-home orders related to prevent further spread of the SARS-CoV-2.

As of April 30, 2020 the U.S. has seen 29,000 deaths and over 1 million confirmed cases. The first safer-at-home policy was implemented in California on March 19, 2020 and many states quickly followed suit; by April 30 all but 8 states had implemented some from of lockdown order. To date, the focus of the debate over safer-at-home orders has been on their efficacy and the tradeoff between lives saved and reduced economic activity. An understudied aspect is the potential externalities of safer-at-home orders on pollution and traffic.

Identifying the causal impact of COVID-19 on pollution is difficult for a number of reasons. For instance, few recent reports and studies provide preliminary (and suggestive) evidence that long-term exposure to fine particulate matter may be associated with an increased risk of COVID-19 death (e.g., Wu et al. (2020)). Moreover, the documented shortage of COVID-19 testing (and the willingness to test) might be related to local pollution level. In this paper, we address these challenges by estimating the impacts of state and county safer-at-home orders instead of the COVID-19 pandemic as a whole, and rely on a differences-in-differences framework. This setting is attractive for at least two reasons. First, not all states (and counties) have implemented safer-at-home orders and there is a great deal of variation in how fast they have been implemented. Second, our identification strategies allow us to tackle issues of reverse causality and omitted variables bias by comparing states (or counties) that implemented safer-at-home orders at different point in time. Our identification assumption is that, conditional on the number of known COVID-19 cases or deaths, the difference in pollution between states (or counties) with and without safer-at-home orders would be constant over time. We relax this assumption by also relying on synthetic control methods, matching counties based on pre-policy pollution and population levels.

We first investigate the impact of safer-at-home orders on pollution. We find that state safer-at-home policies decreased air pollution (PM2.5) by almost 25%, with larger effects for populous counties. This estimated effect is very large and suggest that these policies reduce emissions by almost a half of a standard deviation. Our estimates also suggest the issuance of a state order reduces the number of county-days with an air quality index of code yellow or above by tow-thirds from 26% to 9%. Similarly, we find that county safer-at-home policies have large impacts on pollution, suggesting that local (county) government policies are equally as effective.

We further explore the heterogeneous effects of safer-at-home policies on pollution across county characteristics. We find that the decline in pollution from safer-at-home orders is larger in more urban counties and smaller in counties that voted for President Trump. Our results also indicate that counties with relatively more young people and in states with a larger share of occupations than can be done remotely experience a larger reduction in pollution form these policies.

We also investigate whether safer-at-home orders had an impact on social distancing using cell phone data from Google Inc. Community Mobility reports and Unacast's COVID-19 Toolkit. We first confirm the results of multiple working papers that states' implementation of safer-at-home policies significantly reduced distance traveled.[1] We also explore the heterogeneous impacts of safer-at-home policies on different places visited using the Google cellphone data. We find that safer-at-home policies significantly decrease the number and duration of trips made to places of retail, grocery, parks, transit stations and places of work, and increase time at home.

We further exploit the available data on social distancing to estimate how state lockdowns, conditional on compliance (measured by the social distancing data) reduce pollution. When controlling for visits to retail and recreation, grocery and pharmacy trips, and commuting measures, our estimates decrease by approximately 16 percentage points, suggesting that social distancing partly explain the decline in pollution.

In addition, we estimate the car collision externalities stemming from the safer-at-home orders. We use data from five states where daily county data is available–Alabama, Connecticut, Kentucky, Missouri, and Vermont and identify a large reduction - almost 50% - in traffic collisions after a state order is issued. We also examine fatalities for the three states who report them–Connecticut, Kentucky, and Missouri–with no evidence that fatalities are falling but mild suggestive evidence that the risk of fatalities conditional on a crash is higher.

Lastly, we perform some back of the envelope calculations for the dollar value benefit of our estimated reduction in pollution and car collisions from safer-at-home orders. Using estimates of willingness to pay for pollution reduction based in the U.S. we find the benefit from reduced pollution ranges from $650 million to $13.8 billion. Using estimates of the societal cost of car collisions from the National Highway Traffic Safety Administration we find that the benefit from avoided car collisions to range between $7 billion and $24 billion.

We contribute to a growing literature on the ongoing debate about safe-at-home orders. We mostly relate to theoretical contributions relying on the SIR

[1] See, for instance, Brodeur, Grigoryeva and Kattan (2020), who rely on Unacast data and provide evidence that safer-at-home policies decreased total distance traveled.

epidemiology model (e.g., Alvarez et al. (2020) and Jones et al. (2020)) or recent policy proposals (e.g., Oswald and Powdthavee (2020)). Empirical contributions have analyzed the determinants of safe-at-home orders implementation highlighting a political partisan divide (Allcott et al. (2020); Baccini and Brodeur (2020)), its consequences on mental health (e.g., Brodeur, Clark, Flèche and Powdthavee (2020); Hamermesh (2020)), the economy (e.g., Atkeson (2020); Baker et al. (2020); Béland et al. (2020)) and discrimination (e.g., Schild et al. (2020)). Last, a small literature examines whether lockdowns are successful at preventing contagion (Friedson et al. (2020)) and restricting mobility (Fang et al. (2020)). We believe our study is the first large-scale empirical analysis of the environmental costs of safer-at-home policies in the developed world. The most relevant paper is possibly He et al. (2020), which provides evidence that lockdowns in China decreased PM2.5 by approximately 25%.

Last, our study contributes to a large literature documenting the impacts of pollution and traffic on labor market outcomes.[2] Ostro (1983) links air pollution in the U.S. to lost work days and restricted activity days. Hausman et al. (1984) finds that a one standard deviation increase in suspended particulates is associated with an almost 10% increase in work days lost, after accounting for city fixed effects. Graff Zivin and Neidell (2012) find that Californian farm worker output under piece rate contracts is reduced by 5.6% for a one standard deviation increase in air pollution.[3] Ebenstein et al. (2016) studies show that performance on strictly scheduled yet high stakes exams declines with exam day air pollution - and as a result have lasting impacts on post-secondary educational attainment and earnings. To the extent that air pollution reduces labor supply and its productivity, safer-at-home orders may have a lasting legacy of increased - home based - labor.

Researchers have also identified health consequences of air pollution exposure and extreme traffic; short-term exposure to air pollution impacts heart and lung function (Seaton et al. 1995), irritates the throat and eyes (Pope 3rd 2000), causes headaches (Szyszkowicz 2008) and induces elevated levels of stress hormones (Li et al. 2017).[4] It has also been connected to psychological symptoms such as increased anxiety(Power et al. 2015), reduced pro-social attitude (Lu et al. 2018), depressive sentiment (Szyszkowicz 2007) and increased suicide propensity (Yang et al. 2011). Our finding of decreased pollution thus provides a plausible mechanism for

[2]Our study also adds to a growing literature on the consequences of COVID-19 (Alon et al. (2020); Atkeson (2020); Berger et al. (2020); Binder (Forthcoming); Briscese et al. (2020); Fang et al. (2020); Fetzer et al. (2020); Jones et al. (2020); Ramelli et al. (2020); Stephany et al. (2020); Stock (2020)).

[3]Adhvaryu et al. (2014) study the productivity of garment factory workers in Bangalore and find that a one standard deviation increase in air pollution resulted in a loss of 6% worker efficiency. Chang et al. (2019) study the productivity of white collar (call center) workers in China; higher daily levels of air pollution impact number of calls serviced.

[4]Traffic congestion has been linked to domestic violence (Beland and Brent (2018)), stress (Stutzer and Frey 2008) and unhappiness (Anderson et al. 2016).

the documented decrease in Google Searches for the topic 'Suicide' following the implementation of safer-at-home policies in the U.S. and Europe (Brodeur, Clark, Flèche and Powdthavee (2020)).

The rest of the paper is organized as follows. Section 1 details the data collection, while section 2 describes our methodology. We discuss the impacts of safer-at-home policies on pollution in section 3. In Section 4 we rely on cell phone data to document changes in travel behavior. Section 5 investigates the effects of state and county policies on collisions. Last, Section 7 concludes.

1 Data and Identification Strategy

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 the determinants of implementing stay-at-home orders and our social distancing data. Last, we describe our pollution and collision data.

1.1 COVID-19 Known Cases and Deaths

The first 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 had 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 U.S.

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 knowns cases and deaths per 10,000 inhabitants, respectively. The states of New York and New Jersey had the highest death rate as of mid-April, 2020.

1.2 Safer-at-Home Policy

Figures 1 and 2 present maps of 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. But 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. As of April 30, 2020, 43 states (including the District of Columbia) had implemented some form of lockdown, representing 1,453 counties. 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]

1.3 Social Distancing Data

We extract data on social distancing from the from Google Inc. Community Mobility reports and Unacast's COVID-19 Toolkit. Our main data source is Google, and rely on Unacast's data as a robustness exercise.[6] Table 1 provides summary statistics for our Google and Unacast indexes.

Google Inc. released data on social distancing practices at the daily level for United States Counties.[7] The datasets are presented as percent changes in how visits *and length of stay* to places (like grocery stores or parks) compared to a baseline for the same areas and the same day of the week. The baseline is computed using data from January 3, 2020 to Feb 6, 2020. While the accuracy of cellular tracking data will vary from region to region, our identification is necessarily within region.[8] People's activities are coded into one of six categories: grocery and pharmacy, parks, transit stations, retail and recreation, residential, and workplaces.[9] The data, derived from the Location History of someone's Google Account represents a sample of users - of course this may not reflect the broader population.

We also rely on daily 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 two indexes. Non-essential visits include many places such as cinemas and clothing stores. More details are provided here: `https://www.unacast.com/covid19/social-distancing-scoreboard`. Non-essential locations were determined by Unacast, following guidelines issued by various states.

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

[6]Unacast's data does not allow us to investigate social distance practices by categories, e.g., grocery stores or workplaces. Moreover, the data is unavailable for many counties.

[7]This temporarily available dataset is intended to help remediate the impact of COVID-19. It is available here: `https://www.google.com/covid19/mobility/`.

[8]The data is coded as missing if there are insufficient levels of data to be statistically significant.

[9]Grocery and pharmacy: grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies. Parks: local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens. Transit stations: public transport hubs such as subway, bus, and train stations. Retail and recreation: restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters. Residential: places of residence. Workplaces: places of work.

1.4 Pollution Data

Air pollution data is from *in situ* monitors and provided by AirNow, a partnership between United States agencies.[10] The primary pollutant we use in our analysis is particulate matter with diameters less than 2.5 micrometers - capable of being inhaled and passing 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 also 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.

To aggregate PM2.5 levels from the monitor level to the county level, we assign each county's population weighted centroid to the nearest air quality monitoring station, but only if that station is within 50 kilometers as accurate PM2.5 levels are necessarily local. The minimum distance to a pollution monitoring station is 114 meters, while the mean and median are approximately 25km away.

In Figure 3 we present average weekly PM2.5 levels by county for the week of March 1-7, 2020. This period, prior to any lockdown orders serves as a visual representation of the geographic distribution of air pollution levels. In Figure 4 we present the same PM2.5 measures during the final week of April - after all eventually treated states had implemented a stay at home order.

While a derivative of PM2.5 levels, we also provide results using Air Quality Index data. This unit-less measure ranges from 0 to 500, with a score below 50 representing no harmful levels of air pollution.

1.5 Collision Data

For our analysis on car crashes, we rely on collision data at the county-level from five states: Alabama, Connecticut, Kentucky, Missouri and Vermont. The data were scraped from the data portal Safe Home Alabama, Connecticut Car Crash Data Repository, Kentucky State Police, Missouri State Highway Patrol and the Vermont Public Crash Data Query Tool. The remaining states are excluded for four reasons: (1) data portal unavailable during the pandemic making it impossible to scrap the data; (2) request for data under review (with longer delays due to the pandemic); (3) data unavailable at the county-level; and (4) data available only at the month or year-level.

[10] 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.

Our main variable of interest is the daily number of collisions per county. We also rely on the number of car crash fatalities for one state (Kentucky).

2 Identification Strategy

2.1 Differences-in-Differences

Our hypothesis is that safer-at-home policies decreased PM2.5 concentrations, especially through a decrease of pollution generating behaviors. To investigate this hypothesis, we estimate the following specification:

$$y_{cst} = \alpha + \beta StateSafer_{st} + \lambda CountySafer_{cst} + \gamma c + \delta_t + X'_{cst}\omega + \varepsilon_{cst} \tag{1}$$

where y_{cst} is daily average Particulate Matter 2.5 in μg/m^3 in county c in state s and year t. We include a full set of county dummies γc to control for time-invariant county characteristics and date (e.g., a separate dummy for March 1, 2020, March 2nd, 2020, etc.) dummies δ_t. The time period is January 1st, 2020 through April 30th, 2020. The state-level variable $StateSafer_{st}$ equals one once the state has issued the order and zero for the pre-policy period. 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. The coefficients of interest here is thus λ. For this analysis, the sample is restricted to counties that eventually implement a county order.)

Note that the adoption of safer-at-home policies and timing of adoption msy be endogenously related to the severity of the virus. We thus include, X_{cst}, a vector of county-day level covariates including COVID-19 known cases and deaths per 10,000 people. The county population data comes from 2019 Census estimates. We cluster standard errors at the state-level, corresponding to the primary policy and treatment level.

Our identification assumption is that, conditional on controls, the evolution of PM2.5 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 for treated and untreated counties.

2.2 Synthetic Control Methods

We complement our difference-in-difference estimates with those from a synthetic control methods approach. The main concern with the estimates from the difference-in-difference approach comes from the lack of an appropriate comparison group in the post period. These comparison groups, depending on the date, are either a) counties that have not *yet* had a state order applied to them b) counties that will *never* have a state order applied to them, or c) simply the pre-period of the treated counties. To tease out inference from issues of selection (as in a) and b) or issues of trends (as in c) we turn to the synthetic control method. The synthetic control method addresses this problem by constructing a counterfactual evolution of PM2.5 from a weighted convex combination of others.

This method requires 'donor' counties - counties that are not or are not yet treated - to donate their PM2.5 evolutions to those that are treated. In our application, we restrict donor counties to have populations within 2000 of their treatment county so that we are comparing equally populous areas with each other. We also require counties to have similar pre-COVID PM2.5 average concentrations, within 2 μg/m^3.

To construct our synthetic matching, we follow the steps in Abadie et al. (2010). The idea of this method is to match a treated county (with a state order) to a group of control counties having similar pollution - and population levels - prior to the 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 counties by solving the following optimization problem and finding the optimal vector of weights:

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

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 counties 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 counties.

The pollution level for each synthetic county is constructed as:

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

.

The estimates are put together in the same manner as regressions elsewhere in the paper. Each county is equally weighted. (In Appendix Table A2 we demonstrate the robustness of the synthetic control estimates to the inclusion of weights, since donor states were necessarily similar in population to treatment states.)

3 Stay-Home Orders and Pollution

In this section, we present the main results beginning with our differences-in-differences strategy. We then then provide additional results obtained using synthetic control methods.

3.1 Differences-in-Differences

In Table 2 we present our main result: a state's implementation of a stay-at-home order significantly lowers pollution for its counties.

This table presents estimates of Equation 1 in which we compare counties in states with and without a statewide stay-at-home order. In all columns the dependent variable is PM2.5 concentration. As noted in Section 1, the sample is restricted to counties with a reasonable degree of accuracy in the dependent variable - counties with a population weighted centroid within 50 km of an air pollution monitoring station. We use a total of 1,472 counties in our estimation.

In the first column, we include only date and county fixed effects. The estimate for our statewide stay-at-home order is statistically significant at the 1% level and suggests that the introduction of a state order reduces PM2.5 levels by 1.6 μg/m^3. With a mean of the dependent variable almost 7 (the regression constant in this specification is also the average PM2.5 concentration in the pre-policy period), this suggests the policy decreased air pollution by almost 25%. For additional context, the standard deviation of PM2.5 before any state orders were implemented is 3.4 μg/m^3, suggesting the policy reduces emissions by almost one *half* of a standard deviation.

In the second column, we include the number of confirmed COVID-19 cases per 10,000 people as a control. In the third column, we replace the number of confirmed cases by deaths attributable to COVID-19, again per 10,000 people. The estimates are negative, suggesting that increased cases or increased deaths reduces PM2.5 in a county, although neither are statistically significant at conventional levels.

In the fourth column, we re-estimate the unweighted estimate from column 1 now weighted by county population. In this manner, we are now putting more weight on relatively more populous (and polluted) counties. The inclusion of this weighting increases the effect estimate by more than 50% from 1.6 to 2.5 μg/m^3, suggesting that the decrease in PM2.5 was larger for more populous counties.

In columns 5 and 6, we re-estimate population weighted averages of columns 2 and 3. We find that increased confirmed cases, and in particular higher COVID-19 death rates significantly reduce the air pollution - conditional on a state order being in place. This does not come as a surprise as human behavior and compliance with state orders may be a function of COVID-19 rates. We examine possible mechanisms later.

In Table 3 we conduct a similar but distinct analysis. While in Table 2 the dependent variable was PM2.5 concentration, in Table 3 we change the dependent variable to an indicator that takes a value of one if the PM2.5 level in that county, and on that day, is below the National Ambient Air Quality Standard of 12 $\mu g/m^3$. This analysis is important as Bowe et al. (2019) show that, among a cohort of U.S. veterans, nine causes of death were associated with PM2.5 exposure below standards set by the Environmental Protection Agency.

The specifications and structure of the table remain the same as in Table 2. Instead of measuring the reduction of PM2.5 levels, we now measure increases in *safety*. 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. When state orders are introduced almost all days, for all counties, have acceptably clean air. In column 4, when population weights are introduced, only 74% of county-days have an acceptable PM2.5 level (corresponding to more populated areas having higher levels of ambient air pollution). When the state order is implemented, the proportion of acceptable air days increases by 16 percentage points (a 22% increase).[11]

In Table 4, we examine how county level orders, which are typically implemented before associated state orders, affect ambient pollution levels. The sample is necessarily restricted to counties that at some point implement a county order. In the first column, the effect of the state issuing an order is a reduction of 2.8 $\mu g/m^3$, larger than previous estimate of 1.6 $\mu g/m^3$ (note however, the percentage reduction is essentially the same). While the set of counties that issue their own order have higher pollution levels on average, when their state issues an order their air pollution reduction is proportional to other counties. The second estimate is the *additional* reduction attributable to the county order. The estimate is negative, suggesting further reduction in PM2.5, however it is not statistically significant. Controlling for COVID-19 cases or deaths, as in columns 2 and 3 does not meaningfully disturb this finding.

In columns 4-6, we leverage the time *between* a county and state issue their respective orders (median of 7 days). By restricting the estimation sample to the time period before the state issues the order, we can estimate the effectiveness of the policies available to counties. During this short time frame, the effect of a county order is roughly the same as a state order. Combined with the results from the previous columns, this suggests that counties have the ability to significantly reduce PM2.5 emissions by unilaterally issuing safer-at-home orders, however their

[11] In Appendix Tables A4 and Table A5 we use instead Air Quality Index and an indicator for an acceptable Air Quality Index of below 50, respectively. Estimates are substantively the same.

effectiveness is subsumed by the overarching state authority.

In Appendix Table A1, we further demonstrate the robustness of the effects of state orders on ambient PM2.5 levels to county level government safer-at-home orders. In column 1 we re-produce our main result for all counties. There is a subset of counties that issue their own orders prior to their respective state. In column 2, the constant coefficient indicates this set of counties had higher PM2.5 levels on average. The reduction in PM2.5 levels from a state order is proportionally larger - such that a state order reduces pollution by 25% in counties that did and did not issue their own orders. The estimate of the effect of a county order is negative, but not statistically significant, suggesting that conditional on a state order being present, there is minimal *additional* reduction in PM2.5 from an additional county order being in effect. In column 3, we confirm that state orders were also effective in the majority (1362) counties that did not issue their own order - important as the set of counties that issue their own orders could be driving the results for all counties. The estimated effect of a state order is statistically significant and reassuringly close to the average estimate from column 1. Columns 4 through 6 repeat these exercises controlling for the COVID-19 cases in each county - likely correlated with *when* a county or a state is would issue a state order. The estimated effect size of state orders is reassuringly undisturbed.

3.2 Graphical Evidence

We provide a visual summary of the pollution impact in Figure 5. This figure plots estimated PM2.5 levels at daily intervals pre- and post-statewide order. The Equation is:

$$y_{cst} = \alpha + \sum_{n=-60}^{40} \beta_n (DaysSinceLockdown = n) + \gamma c + \delta_t + \varepsilon_{cst} \tag{2}$$

This specification decomposes the level of PM2.5 by the number of days since (and before) the state order. The regression includes county and date fixed effects, controlling for national level changes in PM2.5 as, for example, the country comes out of winter. We plot the estimated difference between PM2.5 levels compared to the date that the state order was implemented (which is set to zero). The time window is 60 days before to around 45 days after the policy is implemented. The dashed lines represent robust 95% confidence intervals.

Figure 5 shows that PM2.5 levels, within-county, were stable if not increasing from 60 to 15 days prior to the statewide order. Around two weeks before state orders came into effect (on average March 28) we begin to see a reduction in PM2.5 emissions, with an even larger decrease in the days following the implementation.

The negative impact is at its largest at the end of the time window, i.e., 45 days after the safer-at-home implementation, suggesting that adding more days to our sample post-state policy would serve to only increase our point estimates.

Why does pollution register a decrease in the days before the policy? One explanation is that the announcement of the safer-at-home policy typically precedes the implementation by 3–4 days. Another explanation is that a partial lockdown, which includes school and venue closures, may have already been implemented in these counties days before the full safer-at-home date was implemented. It may also reflect people's anticipation of the impending policy date based on their observation of the pandemic or neighboring states that had entered safer-at-home policy earlier. We explore this last possibility in Section 4.

3.3 Synthetic Control Methods

The Differences-in-Differences estimates presented above indicate a large reduction in PM2.5 after a state issues stay-at-home orders. We now turn to our synthetic control methods analysis as a robustness check.

In Appendix Table A2 we present the results of applying synthetic control methods to create, county-by-county, counterfactual levels of PM2.5. This method requires 'donor' counties (counties that will never, or at least do not yet have a state order in place) to donate their PM2.5 time series evolutions to those that are treated. In our application, we restrict donor counties to have populations within 2,000 of their treatment county so that we are comparing equally populous areas with each other. We also require counties to have similar pre-COVID PM2.5 average concentrations, within 2 μg/m^3.[12]

When combined with the observed reduction in PM2.5, the difference between observed (the treated) and the counterfactual (the synthetic control) is very large and statistically significant. In the first column, the dependent variable is this difference; compared to their counterfactual, treated counties reduce their PM2.5 levels by more than 2.5 μg/m^3 on average. The addition of COVID-19 known cases or deaths does not substantially disturb the results. Including populations weights *no longer* increases the effect sizes of the estimates, unsurprising as we now restrict the counterfactual to combinations of counties with *approximately the same population*.

In Appendix Figure A3 we present these results graphically. We see that the levels of pollution are relatively similar for the two sets of counties prior to the state order. Once the state order is implemented, there is a large decrease in pollution in treated counties, which persist over the entire month following the implementation.

[12]Our results are robust to other cut-offs. Estimates available upon request.

Appendix Figures A4 and A5 plot the evolution of PM2.5 in the treated and synthetic control counties, respectively. This split allows us to see whether the decrease in pollution occurs because of treated counties reducing their emission or counterfactual counties increasing their emission. The time period is 30 days prior to 30 days after state orders. We find no changes for counterfactual counties, while the changes for treated counties are strikingly similar to the ones presented in Appendix Figure A3.

3.4 Heterogeneity: Urbanization, Republicans and Work from Home

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 A7. 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.[13] In columns 1–2, we split the sample for over and below county urbanization of 50%, respectively. We find that the estimated decrease is about 33% larger for urban counties than rural counties, confirming our previous finding that more populous counties are more affected by state orders.

In columns 3–4, we restrict the sample for counties in which a majority of voters voted for President Trump during the last 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. This finding is in line with Engle et al. (2020), who document that counties with lower share of votes for republicans comply more with stay-at-home orders.

Columns 5 (6) test the effect of safer-at-home policies for counties with relatively more (less) individuals aged at least 65 years old (split by median). We find that counties with relatively more young people experience a larger decrease in PM2.5, perhaps due to more work being done remotely post-lockdown.

We explore this possibility in columns 7–8. We split the sample into counties within states with above and below median values of the share of occupations that can be done from home. These classifications of the feasibility of working form in a given occupation come from Dingel and Neiman (2020) and code 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 larger decrease in PM2.5.

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

4 Stay-Home Orders and Social Distancing

We now investigate the impacts of safer-at-home policies on trips pattern. We first rely on the Google Inc.'s COVID Community Mobility Report, leveraging the Location History of Android phone users.[14]

In Figure 6, we plot estimates of Equation 2 for the change in retail and recreation time provided by the social distancing data. We see a rising pattern until about 14 days before a state policy is issued. Once the state is 14 days from announcing a state order, the level of trips taken for this non-essential behavior begins reducing, likely reflecting the underlying conditions that ultimately predict a state order being issued. Notably, the day after a state issues an order sees a large and discontinuous jump in the level of retail and recreation visits.

In Figure 7, we present the change in grocery store and pharmacy time. As a behavior its notable that this is often considered essential. This behavior seems to be much less sensitive to underlying conditions - there is very little curvature like that for retail and recreation - but responds swiftly and discontinuously to the state order. (Of anecdotal note is that the day before the state order was issued but after it was announced, there is a sharp *increase* in the visits to grocery stores).

In Figure 8, visitation of local and national parks, there is a generally increasing trend leading up to (and after) the state order.The week following a state order sees a negative dip in visitation, however the estimates quickly become positive. This is unsurprising as it is unclear whether visitation to parks *should* decrease given social distancing orders - this may be left to the state order policy.

In Figure 9, we plot the evolution of trips to transit hubs. These include railway stations as well as subway when available. Some of these visits are undoubtedly long distance trips that are canceled both leading up to and directly after the state issues an order, as well as commuting patterns. This is further examined in Figure 10 which measures trips and length in workplace areas. Around the two weeks leading up to the state order, workplaces trips begin to decrease. The day of the state order sees a large - and discontinuous - fall in time at work. Workplace attendance mirrors PM2.5 levels, decreasing after the order is given.

The final social distance measure is whether people are staying at home - the prescribed place to be under the sort of orders the states issue. We see an evolution that is close to the inverse of what we see for workplace time - about two weeks leading up to a state order to be home, there is some increase in time spent in residence. Compared to the day of implementation, the next day sees a large and discontinuous increase in time spent at home. The trend continues - mirroring in

[14] While estimates vary, Android comprises between 40–60% of the US market share, of approximately 270 million devices.

the literal sense - the trends seen for other social distance measures.

We confirm these findings in Table 5. The dependent variable in the first column is the percentage change in the number and *duration* of trips made, by county to places of retail and recreation. The dependent variable in the second column is grocery store and pharmacy trips. Trips to parks, which includes local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens is the dependent variable in the third column. The fourth column is public transit stations - subway bus and train stations. The fifth and sixth columns' dependent variables are visits to *places* of work (not necessarily working) and places of residence (established during the baseline period in January). Regardless of the measure of social distancing behavior, the implementation of a state order significantly reduces social contact. In other words, safer-at-home policies increase time in residential areas, which increases social distance, but not necessarily familial distance.

These results provide suggestive evidence that safer-at-home policies partly decrease pollution by decreasing the number and duration of trips. In Table 6 we confirm the effects of each of Google Inc.'s COVID social behaviors on ambient PM2.5 levels. Leveraging the entire data period (beginning February 15, 2020) we see that behaviors that take people out of the house (retail and grocery shopping, visiting national parks, commuting to work) all increase ambient pollution levels while more time spent at home reduces PM2.5 concentrations.

In Table 7 we examine how state lockdowns, conditional on reducing these behaviors, reduce pollution levels. Because we do not have data for all counties and all dates (for privacy reasons), the set of counties studied is necessarily a subset of those examined in Table 4. For this reason, in the first column we present the basic specification once again but for our restricted (balanced) sample. For the counties with social distancing data, the introduction of a state order reduces PM2.5 levels by around 1 $\mu g/m^3$. Controlling for visits to retail and recreation, grocery and pharmacy trips, and commuting all reduce (slightly) the estimated effect of the policy, individually and collectively in the final column. The inclusion of these variables decreases the size of our statewide policy by about 16 percentage points.[15]

4.1 Unacast's Social Distancing Indicators

We now test the robustness of our results by using other metrics of distance traveled. More specifically, we examine how state orders affect total distance traveled (ADT) and non-essential visits using Unacast cell phone data.

A number of validation layers occurred to create the metrics. First, ADT correlates well with the number of confirmed COVID-19 cases: the more cases are

[15] We include in our estimation the variables that state lockdowns had an unambiguous effect on, see Figures 6 through 11.

confirmed, the greater the decrease in the average distance traveled an the county-level. For cell phone data in particular, it works independently of information flow disruptions - the metric is unaffected due to cellular inactivity if people are dwelling at home. The metric (while admittedly simple) captures how people adapt their everyday behavior. Working from home, reduction or elimination of trips to entertainment or spare-time facilities, and canceling vacations all reduce travel distance.

Our estimates using Unacast data are presented in Appendix Table A3. The dependent variable is our two indices of total travel distance in columns 1–3 and non-essential visits in columns 4–6, respectively. In the first column, we see that, on average distance travelled fell by 3.3 percentage points under a state order. Columns 2 and 3 add to the model COVID knows case and death rates, respectively. We find that COVID-19 known cases per capita also reduce travel. Unsurprisingly, increased death rates also reduce observed cellular movement patterns. Since it is very plausible that a person could travel 50 feet in one area and meet many people - and in another not meet a soul, we examine the number of non-essential places visited in columns 4–6. Results are quantitatively similar - state orders reduce the likelihood to visit non-essential places by 6 percentage points.

5 Stay-Home Orders and Collision

Social distancing can result in fewer cars on the road, reducing emissions of air pollution and also reducing the number of collisions or fatalities experienced. Motor vehicle collisions are one of the leading causes of deaths for Americans - beaten only by heart disease, malignant neoplasms and unintentional poisoning. (Both heart disease and malignant neoplasms have been connected to PM2.5 exposure.) In this way, state orders may save even more lives than intended. We collected traffic collisions data at the county-day level for Alabama, Connecticut, Kentucky, Missouri, and Vermont. There are an average of 6.2 car crashes from January 22nd, 2020 through April 30th, 2020.

In Table 8, we estimate the effects of state orders on the collision incidence rate in a county, per day. We present the incidence report ratios of a Poisson count model with county and date fixed effects. In the first column, we estimate that a state order reduces the incidence of collisions by almost two thirds. Taking the approximately 6 crashes per day, this results in a reduction of 4 collisions per day, *per county*. 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 three measures of social distancing: grocery and pharmacy, retail and recreation, and workplaces. Introducing these measures in the model helps accounting for the direct channels through which the state orders should be operating. We find that the effect estimate for a state order down to 45% (from about 60%).

Overall, these results suggest that safer-at-home policies had very large impacts on traffic collision, in part due to a decrease in visits to places such as groceries and workplaces.

Last, we rely on fatalities for one state, Kentucky. The estimates are presented in Appendix Table A8. In all columns, the estimated effect of a state order is statistically significant - the introduction of a state order drastically reduces fatal collisions. In the second column, we control for the count of collisions. As expected, more collisions lead to an increase in fatal collisions. The estimated effect of fatal collisions falls to around a one-half reduction. Increased COVID-19 deaths correspond to greater fatality rates as well.

6 Interpretation

In this section, we provide back of the envelope calculations of the 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. Currie et al. (2015) exploit the effect of toxic plant openings to estimate the impact of air quality on house values and lifetime earnings due to depressed birth weights. Recent work by Ito and Zhang (2020) using purchases of air purifiers in China suggests that the WTP for 1 μg/m^3 reduction of PM10 is \$1.34 annually. Chay and Greenstone (2005) find that the elasticity of housing values to particulates ranges from -0.2 to -0.35. Deschênes et al. (2017) estimate the WTP for nitrogen oxides reductions. Barwick et al. (2017) estimate a lower bound of the annual WTP for a 10 μg/m^3 reduction in PM2.5 in China is \$9.25 per household. 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 of up to \$300.

Our estimates from Table 2 indicate that the introduction of safer-at-home orders decreased pollution by 1.6–2.5 μg/m^3. Despite the estimates being for PM10, if we were to apply the WTP estimates of \$ 1.34 per 10 μg/m^3 annually reduction from Ito and Zhang (2020) to our findings and prorate it for the average number of lockdown days (85,119 county-days / 1453 counties = 58.6 days), we obtain estimates of \$0.034–\$0.054 per household. As there are 114,951,213 households in the U.S. that are affected by safer-at-home orders (Census Estimates, American Community Survey 2018), that translates to an estimated benefit ranging from \$3.9 million to \$6 million. If instead we use the PM2.5 specific estimates of WTP from Barwick et al. (2017), the estimated benefit falls between \$27.3 million to \$42.6

million.

Borrowing from Bayer et al. (2016) who find American home owners are willing to pay between \$60-\$300 annually for a 10% reduction in one pollutant, the WTP associated with our estimated 25% reduction in PM2.5 could be as high as \$150-\$750 annually per household.[16] Furthermore, Bayer et al. (2009) estimate that the marginal WTP for a 1 μg/m^3 reduction in PM10 for 1 year to be \$22 per household.

Using these estimates of WTP from the more appropriate American samples we instead find estimated benefits of \$650 million to \$1 billion using the adapted WTPs from Bayer et al. (2009), and \$2.7 billion to \$13.8 billion using the adapted estimates from Bayer et al. (2016). These estimations vary widely, no doubt due to the many assumptions necessary to compute figures at such an aggregate level. However they serve to give a sense of the scale of the possible environmental benefits these orders have.

There are extensive costs associated with traffic collisions, from congestion impacts; to medical and repair bills; to loss of life. We can generate rough estimates of the benefits of reduced collisions using 2013 estimates provided by the analytics company ISO that the average collision claim was \$3,144 USD (about \$3,500 USD in 2020): http://www.rmiia.org/auto/traffic_safety/Cost_of_crashes.asp. Alternatively, the National Highway Traffic Safety Administration (NHTSA) estimated that the economic cost of the 13.6 million motor vehicle crashes was \$242 billion , for an average cost of \$17,794 (2010 dollars, \$ 21,054 in 2020) per crash.[17] When accounting for quality-of-life valuations, the estimates are \$836 billion in costs, for an average of \$61,470 (2010 dollars, \$72,732 in 2020) per crash.

If taken to the national-level and not restricting to our PM2.5 data, 2,628 distinct counties were subject to a state order by April 30th, 2020. Their combined total of lockdown-days was an estimated 85,119. If the reduction in the fi

ve states in our sample is representative, this suggests more than 340,000 accidents have been avoided by April 30th, 2020. This is an under-estimate, as some counties had implemented an order before their state governments. Multiplying this figure by \$3,500 yields \$1.2 billion dollars in avoided collision claims. Using the numbers from the NHTSA gives approximately \$7–\$24 billion 2020 (depending on the consideration of quality-of-life valuations) as a result of safer-at-home orders, so far.

[16] While 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 dollars). Other WTP estimates discussed in Chattopadhyay (1999) for particulate pollution reductions in the Chicago Area range from \$0 to \$366 in 1982-84 dollars.

[17] See https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812013.

7 Conclusion

Governments and researchers have only recently begun to investigate the consequences of safer-at-home policies (and other similar policies). In many respects, safer-at-home policies have been shown to have negative impacts on societies by increasing mental health distress and exacerbating the economic impacts of COVID-19, for instance. This paper represents a first step toward understanding the unintended positive effects of safer-at-home policies on pollution, traffic and car crashes.

We pair a differences-in-differences framework and synthetic control methods with rich cellular tracking and high frequency air pollution data. We find that state and U.S. county safer-at-home policies are successful in encouraging social distance; beginning the day of the policy trips outside the home are sharply decreased while time in residence rises sharply. With less vehicle traffic, we also find a 50% reduction in vehicular collisions; one of the leading causes of death in the United States. We calculate that the benefits from avoided car collisions could range from $7 billion to $24 billion while the benefits from reduced pollution could range from $650 million to $13.8 billion.

Taken together, the reduction in mobility results in an approximately 25% reduction in Particulate Matter (PM2.5) concentrations. While 26% of county-days have an air quality index of code yellow or above, the issuance of a state order reduces the incidence by two-thirds to 9%. We also find that local (county) government policies are equally as effective as their overarching state orders, suggesting communities desiring rapid responses were capable of reducing behaviors.

Our paper raises broader questions around the difficulty of estimating the entire set of costs and benefits of safer-at-home policies. As more data on COVID-19 cases and deaths become available, it will be possible to better estimate how many lives were saved (Hsiang et al. (2020)). But the unintended consequences and large sphere of domains impacted by social distancing behavior will make it difficult to estimate the actual costs and benefits of lockdowns.

References

Abadie, A., Diamond, A. and Hainmueller, J.: 2010, Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program, *Journal of the American statistical Association* **105**(490), 493–505.

Adhvaryu, A., Kala, N. and Nyshadham, A.: 2014, Management and Shocks to Worker Productivity: Evidence from Air Pollution Exposure in an Indian Garment Factory. mimeo University of Michigan.

Allcott, H., Boxell, L., Conway, J., Gentzkow, M., Thaler, M. and Yang, D. Y.: 2020, Polarization and Public Health: Partisan Differences in Social Distancing During the Coronavirus Pandemic. NBER Working Paper 26946.

Alon, T., Doepke, M., Olmstead-Rumsey, J. and Tertilt, M.: 2020, The Impact of COVID-19 on Gender Equality. NBER Working Paper 26947.

Alvarez, F. E., Argente, D. and Lippi, F.: 2020, A Simple Planning Problem for Covid-19 Lockdown. NBER Working Paper 26981.

Anderson, M. L., Lu, F., Zhang, Y., Yang, J. and Qin, P.: 2016, Superstitions, Street Traffic, and Subjective Well-Being, *Journal of Public Economics* **142**, 1–10.

Atkeson, A.: 2020, What Will be the Economic Impact of COVID-19 in the US? Rough Estimates of Disease Scenarios. Federal Reserve Bank of Minneapolis Staff Report 595.

Baccini, L. and Brodeur, A.: 2020, Explaining Governors' Response to the COVID-19 Pandemic in the United States. IZA Discussion Paper 13137.

Baker, S. R., Farrokhnia, R. A., Meyer, S., Pagel, M. and Yannelis, C.: 2020, How Does Household Spending Respond to an Epidemic? Consumption During the 2020 COVID-19 Pandemic. NBER Working Paper 26949.

Barwick, P. J., Li, S., Rao, D. and Zahur, N. B.: 2017, Air pollution, health spending and willingness to pay for clean air in china, *SSRN Electronic Journal. doi* **10**.

Bayer, P., Keohane, N. and Timmins, C.: 2009, Migration and hedonic valuation: The case of air quality, *Journal of Environmental Economics and Management* **58**(1), 1–14.

Bayer, P., McMillan, R., Murphy, A. and Timmins, C.: 2016, A dynamic model of demand for houses and neighborhoods, *Econometrica* **84**(3), 893–942.

Beland, L.-P. and Brent, D. A.: 2018, Traffic and Crime, *Journal of Public Economics* **160**, 96–116.

Béland, L.-P., Brodeur, A. and Wright, T.: 2020, The Short-Term Economic Consequences of COVID-19: Exposure to Disease, Remote Work and Government Response. IZA Discussion Paper 13159.

Berger, D. W., Herkenhoff, K. F. and Mongey, S.: 2020, An SEIR Infectious Disease Model with Testing and Conditional Quarantine. NBER Working Paper 26901.

Binder, C.: Forthcoming, Coronavirus Fears and Macroeconomic Expectations, *Review of Economics and Statistics* .

Bowe, B., Xie, Y., Yan, Y. and Al-Aly, Z.: 2019, Burden of Cause-Specific Mortality Associated With PM2. 5 Air Pollution in the United States, *JAMA Network Open* **2**(11), e1915834–e1915834.

Briscese, G., Lacetera, N., Macis, M. and Tonin, M.: 2020, Compliance with COVID-19 Social-Distancing Measures in Italy: The Role of Expectations and Duration. NBER Working Paper 26916.

Brodeur, A., Clark, A. E., Flèche, S. and Powdthavee, N.: 2020, COVID-19, Lockdowns and Well-Being: Evidence from Google Trends. IZA Discussion Paper 13204.

Brodeur, A., Grigoryeva, I. and Kattan, L.: 2020, Stay-At-Home Orders, Social Distancing and Trust.

Chang, T. Y., Graff Zivin, J., Gross, T. and Neidell, M.: 2019, The Effect of Pollution on Worker Productivity: Evidence from Call Center Workers in China, *American Economic Journal: Applied Economics* **11**(1), 151–72.

Chattopadhyay, S.: 1999, Estimating the demand for air quality: new evidence based on the chicago housing market, *Land Economics* pp. 22–38.

Chay, K. Y. and Greenstone, M.: 2005, Does air quality matter? evidence from the housing market, *Journal of political Economy* **113**(2), 376–424.

Currie, J., Davis, L., Greenstone, M. and Walker, R.: 2015, Environmental health risks and housing values: evidence from 1,600 toxic plant openings and closings, *American Economic Review* **105**(2), 678–709.

Deschênes, O., Greenstone, M. and Shapiro, J. S.: 2017, Defensive investments and the demand for air quality: Evidence from the nox budget program, *American Economic Review* **107**(10), 2958–89.

Dingel, J. I. and Neiman, B.: 2020, How many jobs can be done at home?, *Technical report*, National Bureau of Economic Research.

Ebenstein, A., Lavy, V. and Roth, S.: 2016, The Long-run Economic Consequences of High-stakes Examinations: Evidence from Transitory Variation in Pollution, *American Economic Journal: Applied Economics* **8**(4), 36–65.

Engle, S., Stromme, J. and Zhou, A.: 2020, Staying at Home: Mobility Effects of Covid-19, *CEPR Covid Economics: Vetted and Real-Time* **4**, 86–102.

Fang, H., Wang, L. and Yang, Y.: 2020, Human Mobility Restrictions and the Spread of the Novel Coronavirus (2019-nCoV) in China. NBER Working Paper 26906.

Fetzer, T., Hensel, L., Hermle, J. and Roth, C.: 2020, Coronavirus Perceptions and Economic Anxiety.

Friedson, A. I., McNichols, D., Sabia, J. J. and Dave, D.: 2020, Did California's Shelter-in-Place Order Work? Early Coronavirus-Related Public Health Effects. NBER Working Paper 26992.

Graff Zivin, J. and Neidell, M.: 2012, The Impact of Pollution on Worker Productivity, *American Economic Review* **102**(7), 3652–73.

Hamermesh, D. S.: 2020, Lockdowns, Loneliness and Life Satisfaction. IZA Discussion Paper 13140.

Harrison, D. and Rubinfeld, D. L.: 1978, The air pollution and property value debate: some empirical evidence, *The Review of Economics and Statistics* pp. 635–638.

Hausman, J. A., Ostro, B. D. and Wise, D. A.: 1984, Air Pollution and Lost Work.

He, G., Pan, Y. and Tanaka, T.: 2020, COVID-19, City Lockdowns, and Air Pollution: Evidence from China.

Hsiang, S., Allen, D., Annan-Phan, S., Bell, K., Bolliger, I., Chong, T., Druckenmiller, H., Hultgren, A., Huang, L. Y., Krasovich, E. et al.: 2020, The Effect of Large-Scale Anti-Contagion Policies on the Coronavirus (COVID-19) Pandemic. medRxiv.

Ito, K. and Zhang, S.: 2020, Willingness to pay for clean air: Evidence from air purifier markets in china, *Journal of Political Economy* **128**(5), 000–000.

Jones, C. J., Philippon, T. and Venkateswaran, V.: 2020, Optimal Mitigation Policies in a Pandemix: Social Distancing and Working from Home. NBER Working Paper 26984.

Li, H., Cai, J., Chen, R., Zhao, Z., Ying, Z., Wang, L., Chen, J., Hao, K., Kinney, P. L., Chen, H. et al.: 2017, Particulate Matter Exposure and Stress Hormone Levels: A Randomized, Double-blind, Crossover Trial of Air Purification, *Circulation* **136**(7), 618–627.

Lu, J. G., Lee, J. J., Gino, F. and Galinsky, A. D.: 2018, Polluted Morality: Air Pollution Predicts Criminal Activity and Unethical Behavior, *Psychological Science* **29**(3), 340–355.

Ostro, B. D.: 1983, The Effects of Air Pollution on Work Loss and Morbidity, *Journal of Environmental Economics and Management* **10**(4), 371–382.

Oswald, A. J. and Powdthavee, N.: 2020, The Case for Releasing the Young from Lockdown: A Briefing Paper for Policymakers. IZA Discussion Paper 13113.

Pope 3rd, C.: 2000, Epidemiology of Fine Particulate Air Pollution and Human Health: Biologic Mechanisms and Who's at Risk?, *Environmental Health Perspectives* **108**(suppl 4), 713–723.

Power, M. C., Kioumourtzoglou, M.-A., Hart, J. E., Okereke, O. I., Laden, F. and Weisskopf, M. G.: 2015, The Relation Between Past Exposure to Fine Particulate Air Pollution and Prevalent Anxiety: Observational Cohort Study, *BMJ* **350**, h1111.

Ramelli, S., Wagner, A. F. et al.: 2020, Feverish Stock Price Reactions to COVID-19. Swiss Finance Institute No 20-12.

Schild, L., Ling, C., Blackburn, J., Stringhini, G., Zhang, Y. and Zannettou, S.: 2020, "Go Eat a Bat, Chang!": An Early Look on the Emergence of Sinophobic Behavior on Web Communities in the Face of COVID-19. arXiv preprint arXiv:2004.04046.

Seaton, A., Godden, D., MacNee, W. and Donaldson, K.: 1995, Particulate Air Pollution and Acute Health Effects, *Lancet* **345**(8943), 176–178.

Stephany, F., Stoehr, N., Darius, P., Neuhäuser, L., Teutloff, O. and Braesemann, F.: 2020, The CoRisk-Index: A Data-Mining Approach to Identify Industry-Specific Risk Assessments Related to COVID-19 in Real-Time. arXiv preprint arXiv:2003.12432.

Stock, J. H.: 2020, Data Gaps and the Policy Response to the Novel Coronavirus. NBER Working Paper 26902.

Stutzer, A. and Frey, B. S.: 2008, Stress that Doesn't Pay: The Commuting Paradox, *Scandinavian Journal of Economics* **110**(2), 339–366.

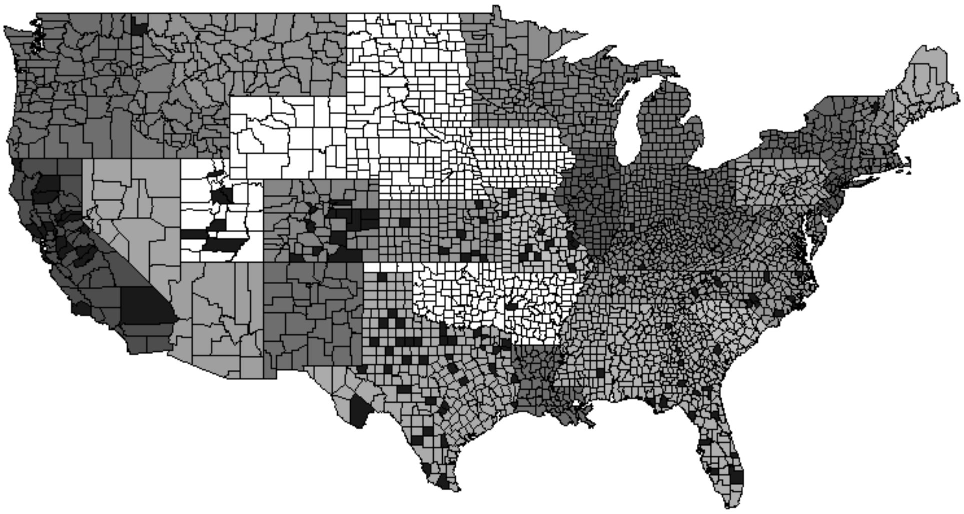
Szyszkowicz, M.: 2007, Air Pollution and Emergency Department Visits for Depression in Edmonton, Canada, *International Journal of Occupational Medicine and Environmental Health* **20**(3), 241–245.

Szyszkowicz, M.: 2008, Air Pollution and Daily Emergency Department Visits for Headache in Montreal, Canada, *Headache: The Journal of Head and Face Pain* **48**(3), 417–423.

Wu, X., Nethery, R. C., Sabath, B. M., Braun, D. and Dominici, F.: 2020, Exposure to Air Pollution and COVID-19 Mortality in the United States. medRxiv.

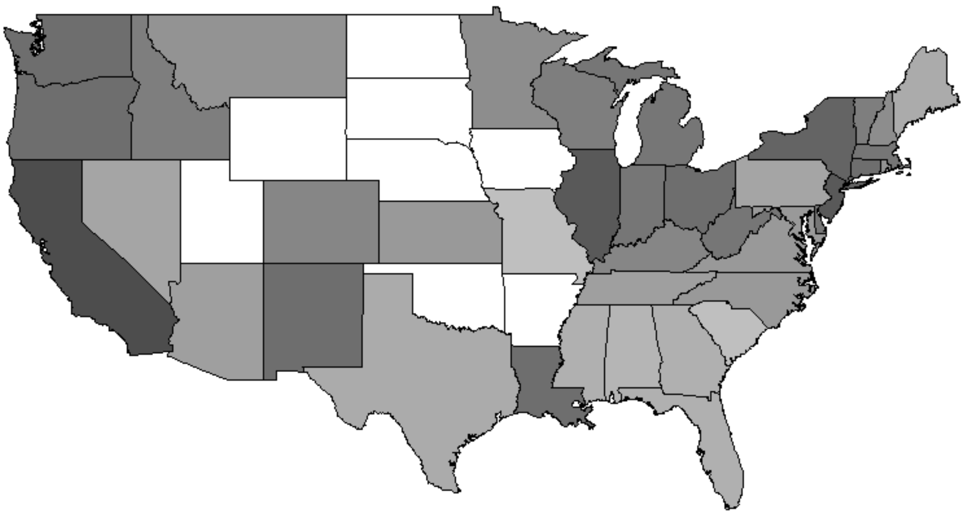
Yang, A. C., Tsai, S.-J. and Huang, N. E.: 2011, Decomposing the Association of Completed Suicide with Air Pollution, Weather, and Unemployment Data at Different Time Scales, *Journal of Affective Disorders* **129**(1-3), 275–281.

Figure 1: Counties that Issued an Order



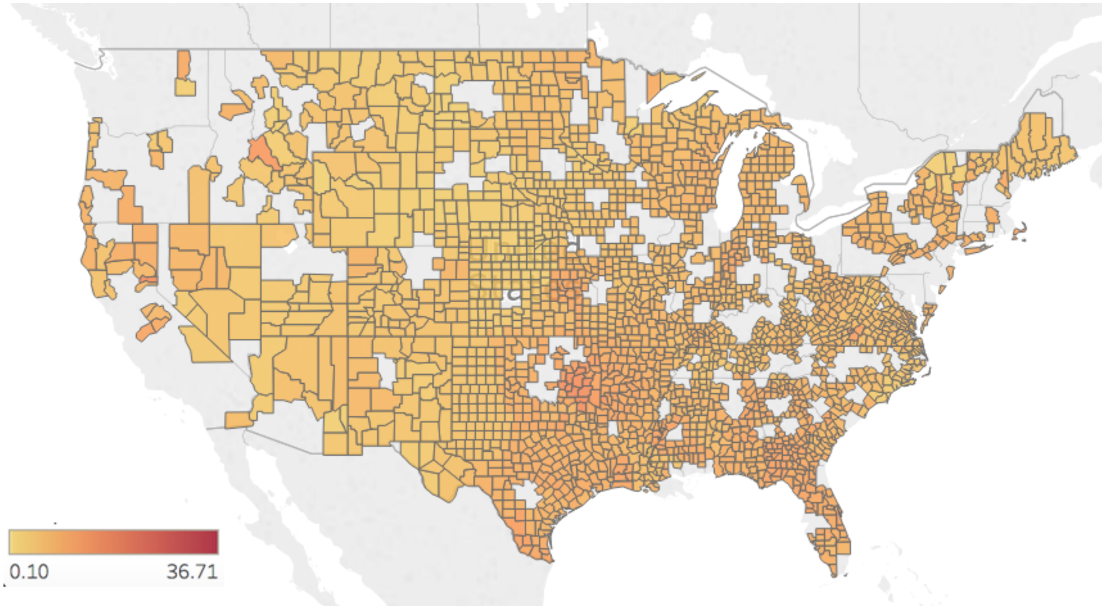
Notes: This map presents counties and states that issued an order prior to April 30, 2020. Counties that issued their own order prior to their state shaded darkest. For states, the darker the fill, the earlier the state issued the order. States in white did not issue an order.

Figure 2: States that Issued a Lockdown



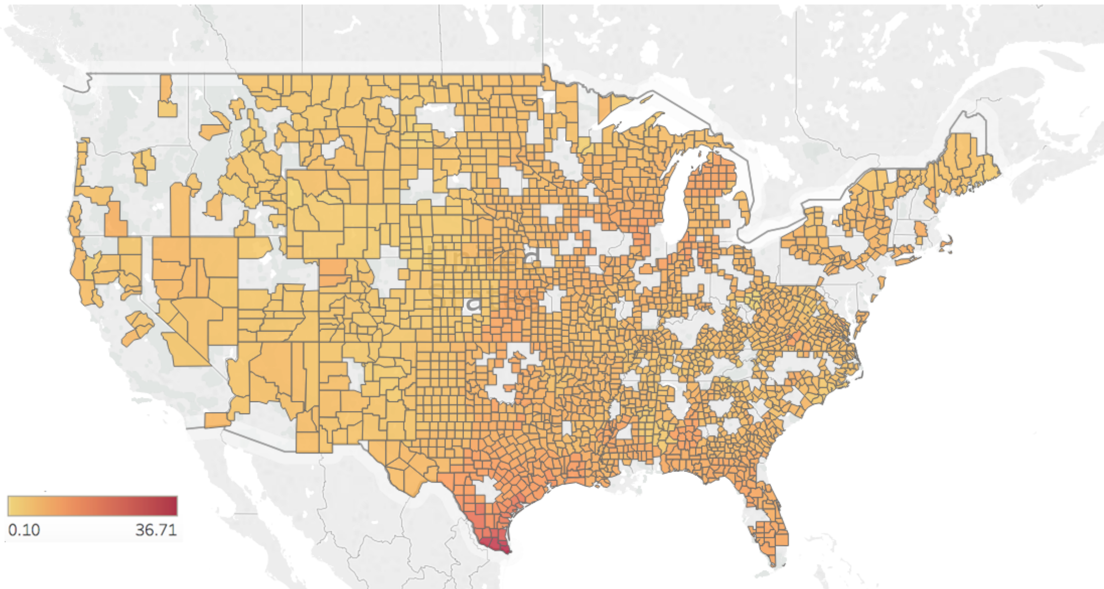
Notes: This map presents states that issued an order prior to April 30, 2020. The darker the fill, the earlier the state issued the order. States in white did not issue an order.

Figure 3: Weekly Average PM2.5 Concentrations March 1-7, 2020



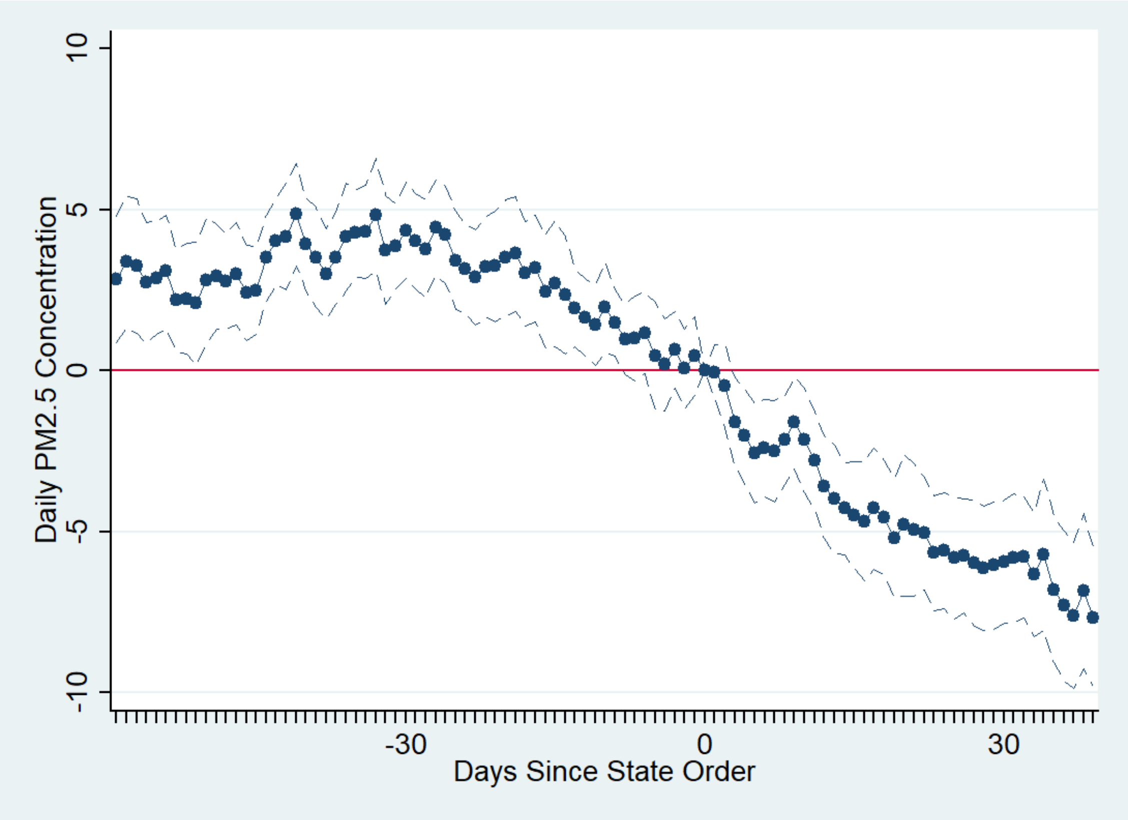
Notes: This map presents PM2.5 concentrations for a baseline week of March 1-7. PM2.5 measures for counties with a population weighted centroid within 50km of an air quality monitoring station.

Figure 4: Weekly Average PM2.5 Concentrations April 19-25, 2020



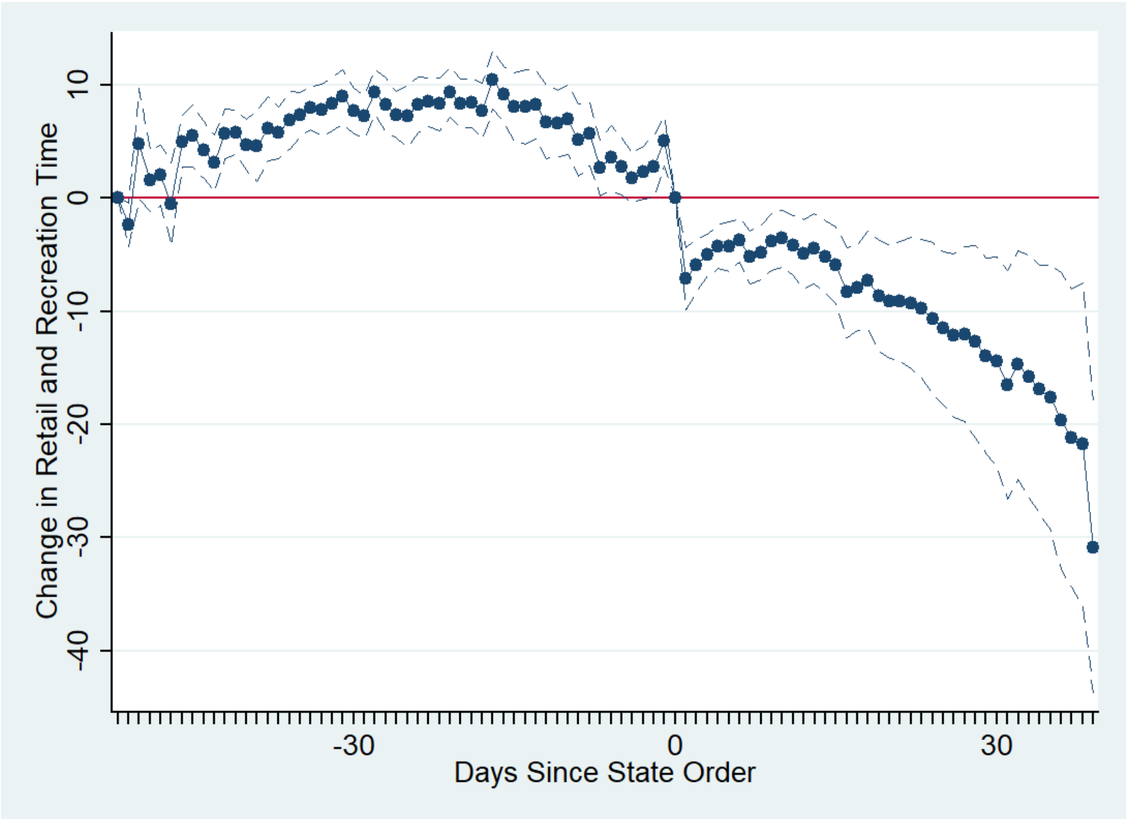
Notes: This map presents PM2.5 concentrations for near end of April 2020. PM2.5 measures for counties with a population weighted centroid within 50km of an air quality monitoring station.

Figure 5: PM2.5 Concentrations Over Time



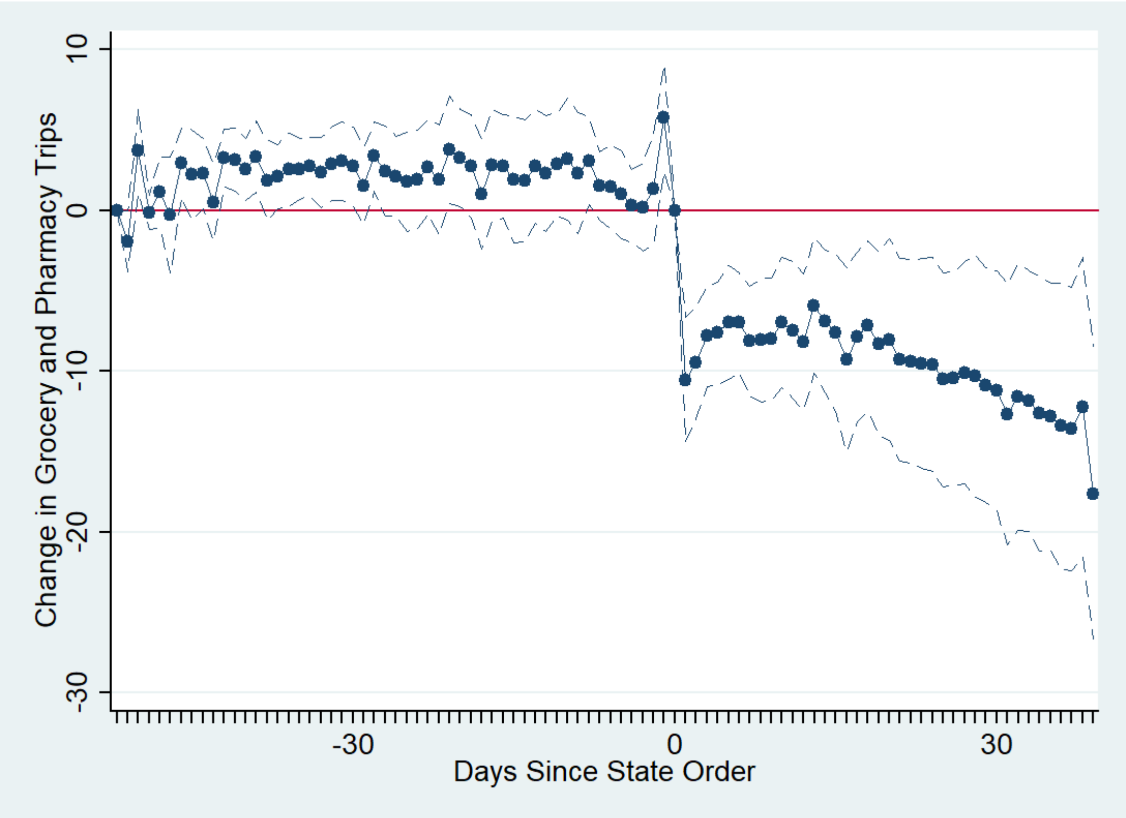
Notes: This figure presents regression coefficients for PM2.5 concentrations corresponding to number of days before/after state order issued. Date and county fixed effects included. The baseline date is presented with a red line. Confidence intervals at 95% presented.

Figure 6: Retail and Recreation



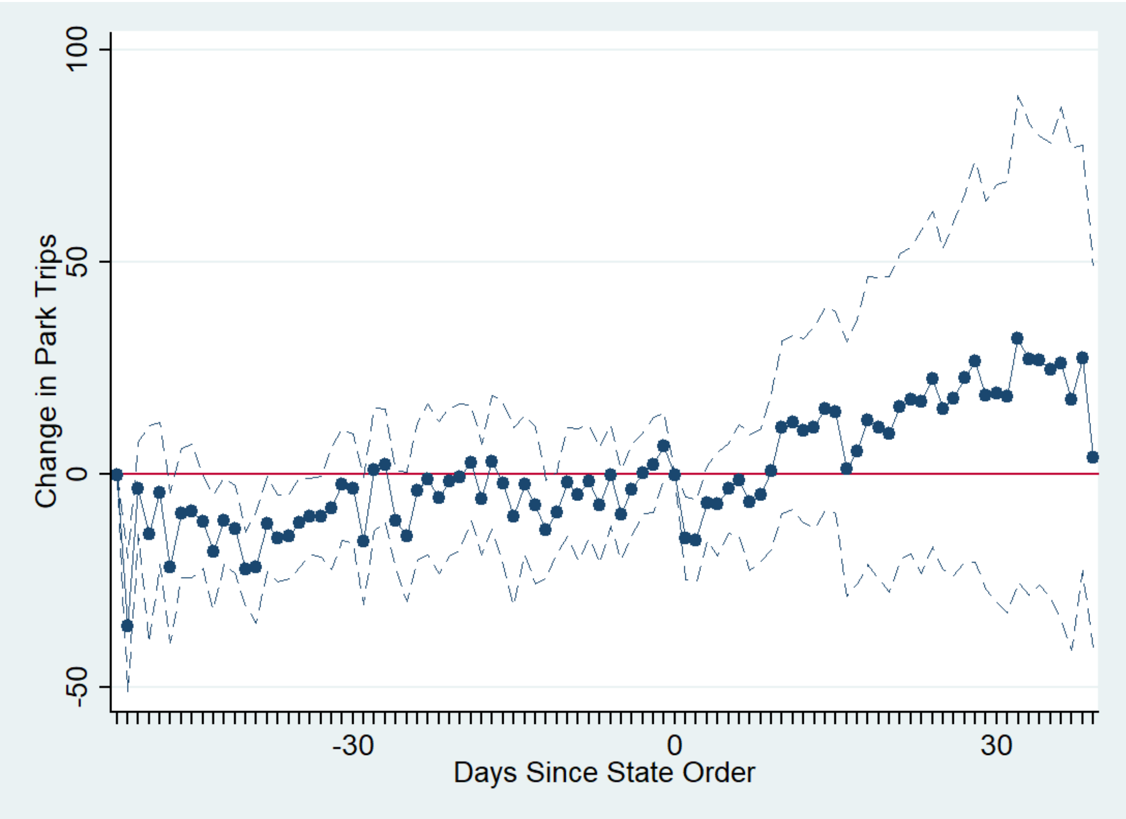
Notes: This figure presents regression coefficients for Retail and Recreation trips corresponding to number of days before/after state order issued. Date and county fixed effects included. The baseline date is presented with a red line. Confidence intervals at 95% presented.

Figure 7: Grocery and Pharmacy



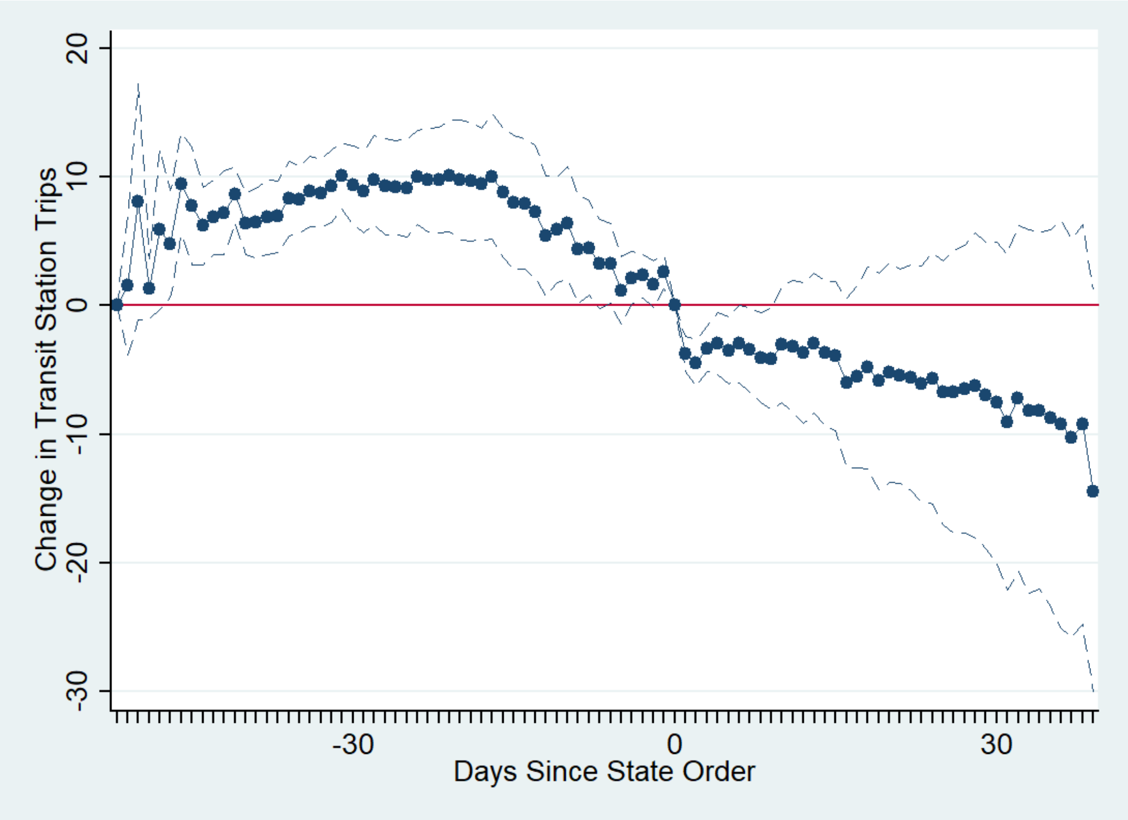
Notes: This figure presents regression coefficients for Pharmacy and Grocery store trips corresponding to number of days before/after state order issued. Date and county fixed effects included. The baseline date is presented with a red line. Confidence intervals at 95% presented.

Figure 8: Parks



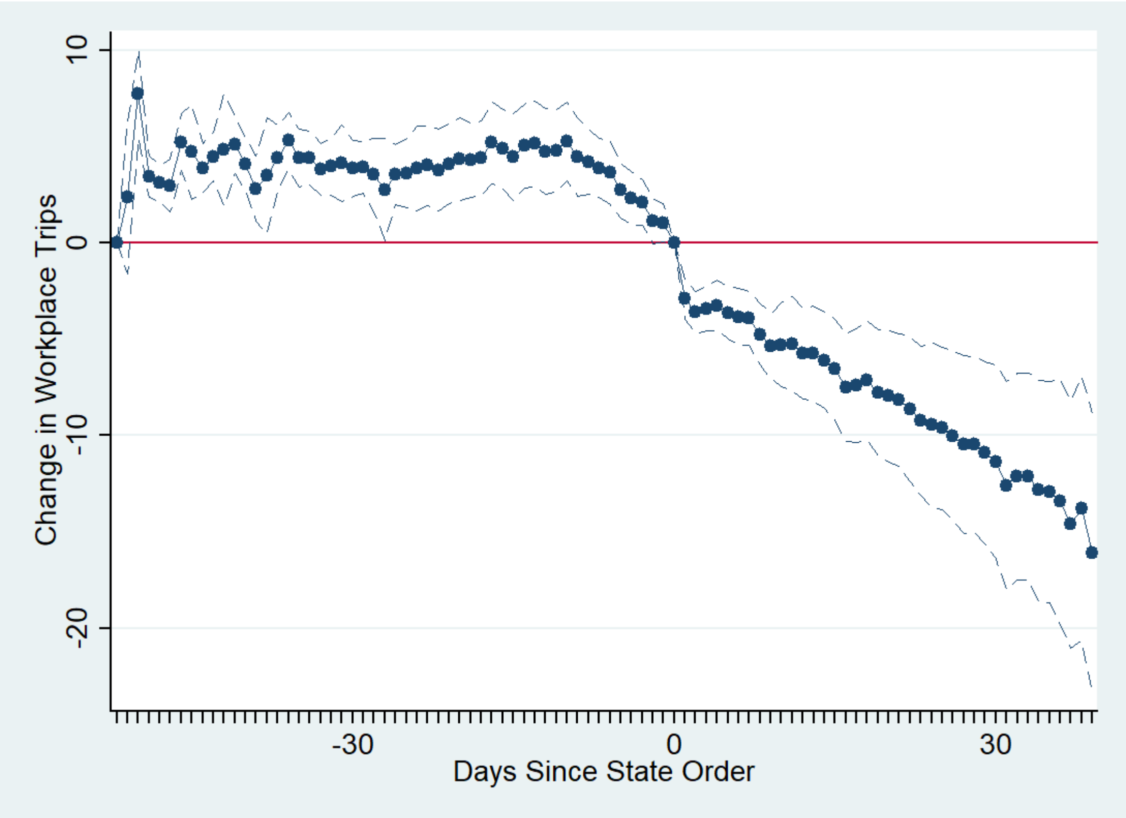
Notes: This figure presents regression coefficients for trips to parks such as local and national corresponding to number of days before/after state order issued. Date and county fixed effects included. The baseline date is presented with a red line. Confidence intervals at 95% presented.

Figure 9: Transit Stations



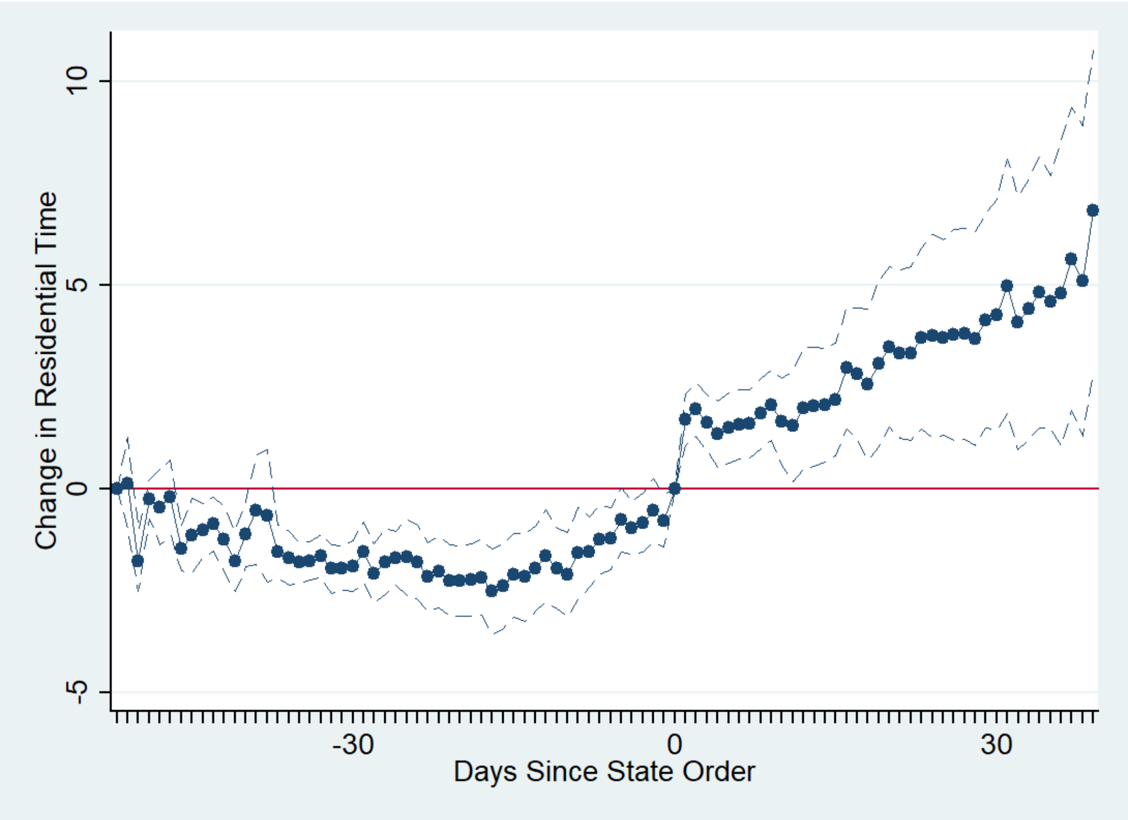
Notes: This figure presents regression coefficients for trips to and from transit hubs, such as raily and bus stations, corresponding to number of days before/after state order issued. Date and county fixed effects included. The baseline date is presented with a red line. Confidence intervals at 95% presented.

Figure 10: Workplaces



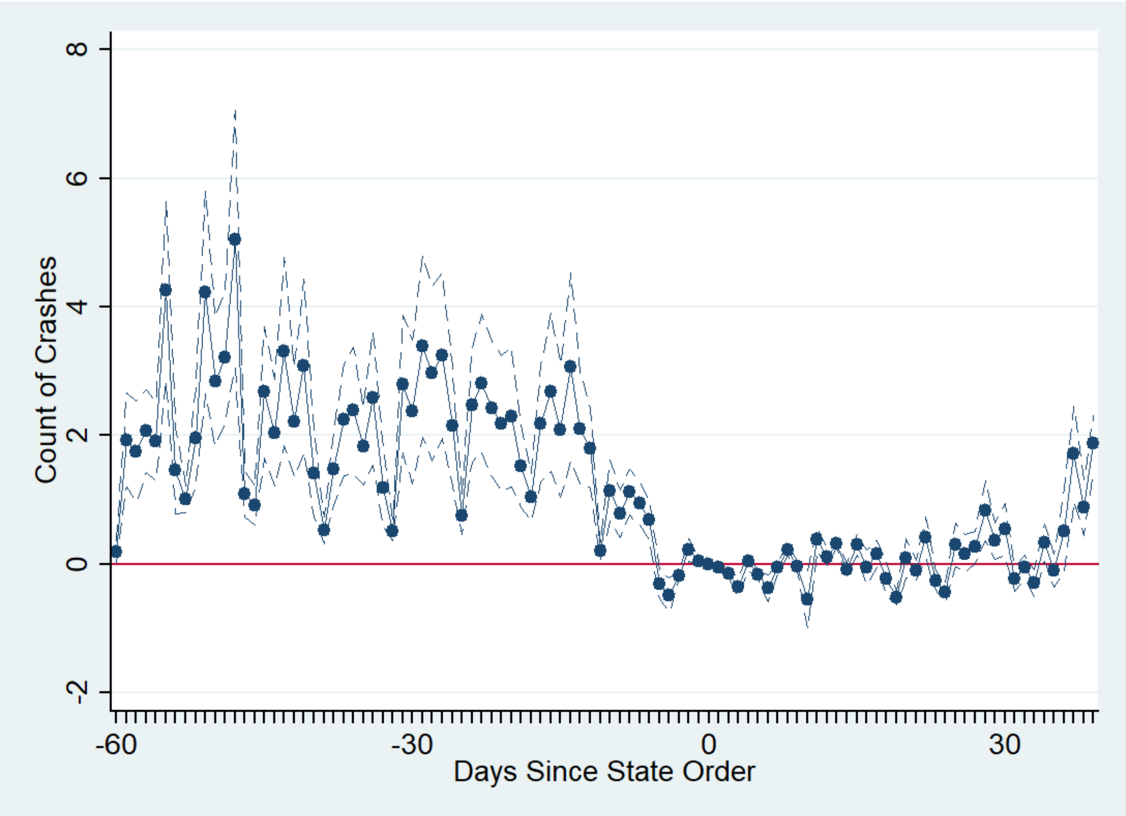
Notes: This figure presents regression coefficients for trips to and from workplaces corresponding to number of days before/after state order issued. Date and county fixed effects included. The baseline date is presented with a red line. Confidence intervals at 95% presented.

Figure 11: Residence



Notes: This figure presents regression coefficients for trips to and from residences corresponding to number of days before/after state order issued. Date and county fixed effects included. The baseline date is presented with a red line. Confidence intervals at 95% presented.

Figure 12: Traffic Collisions



Notes: This figure presents regression coefficients for collisions corresponding to number of days before/after state order issued. Date and county fixed effects included. The baseline date is presented with a red line. Confidence intervals at 95% presented.

Table 1: Summary Statistics

	Count	Mean	Std. Dev.	Min	Max
Pollution variable:					
PM25	380,303	6.55	3.90	0	83.2
Google variables:					
Grocery and pharm.	149,891	0.44	15.9	-81	174
Parks	50,077	8.81	41.5	-91	324
Residential	90,041	8.8	8.7	-11	38
Retail and rec.	155,908	-13.6	24.6	-100	226
Transit and stations	75,883	-15.02	24.4	-91	222
Workplaces	192,064	-20.9	19.5	-81	43
Unacast variables:					
Travel distance	91,206	-0.22	0.18	-0.91	1.34
Non-essential visits	108,013	-0.35	0.26	-1	1.68

Notes: Authors' calculations. PM2.5 is 24-hour daily concentration of PM2.5 in $\mu g/m^3$. The travel distance metric and visit metric are from the Unacast Social Distancing Scoreboard. Retail and recreation, grocery and pharmacy, parks, transit stations, workplaces and residential from Google Community Mobility Report.

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

	(1) PM2.5	(2) PM2.5	(3) PM2.5	(4) PM2.5	(5) PM2.5	(6) PM2.5
State Order	-1.610***	-1.612***	-1.613***	-2.472***	-2.481***	-2.504***
	(0.440)	(0.440)	(0.441)	(0.751)	(0.742)	(0.737)
COVID-19 Cases		-0.005			-0.009*	
		(0.004)			(0.005)	
COVID-19 Deaths			-0.046			-0.149***
			(0.067)			(0.049)
Constant	6.780***	6.780***	6.780***	10.841***	10.841***	10.841***
	(0.827)	(0.827)	(0.827)	(1.865)	(1.873)	(1.872)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	162471	162471	162471	162471	162471	162471
Counties	1472	1472	1472	1472	1472	1472

Notes: State orders significantly reduce PM2.5. The dependent variable is average daily PM2.5 concentration at the county-level. The time period is January 1st, 2020 through April 30th, 2020. COVID-19 known cases and deaths per 10,000 people. Population 2019 population estimates. Standard errors reported in parentheses, clustered at the state-level. All columns include county and date fixed effects. Sample restricted to counties within 50km of an air pollution monitoring station. Column 4–6 replicate columns 1–3 using population weights. (*** p<0.01, ** p<0.05, * p<0.1.)

Table 3: State Orders and Polluted Days

	(1)	(2)	(3)	(4)	(5)	(6)
	<12 $\frac{\mu g}{m^3}$	<12 $\frac{\mu g}{m^3}$	<12 $\frac{\mu g}{m^3}$	<12 $\frac{\mu g}{m^3}$	<12 $\frac{\mu g}{m^3}$	<12 $\frac{\mu g}{m^3}$
State Order	0.093***	0.094***	0.094***	0.161***	0.161***	0.162***
	(0.030)	(0.030)	(0.030)	(0.051)	(0.050)	(0.050)
COVID-19 Cases		0.000			0.000	
		(0.000)			(0.000)	
COVID-19 Deaths			0.003			0.006*
			(0.004)			(0.003)
Constant	0.892***	0.892***	0.892***	0.738***	0.738***	0.738***
	(0.038)	(0.038)	(0.038)	(0.077)	(0.077)	(0.077)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	162471	162471	162471	162471	162471	162471
Counties	1472	1472	1472	1472	1472	1472

Notes: State orders significantly reduce polluted days. The dependent variable takes a value of 1 if PM2.5 is below the Annual National Ambient Air Quality Standard of 12 μg/m^3. The time period is January 1st, 2020 through April 30th, 2020. COVID-19 known cases and deaths per 10,000 people. Population 2019 population estimates. Standard errors reported in parentheses, clustered at the state-level. All columns include county and date fixed effects. Sample restricted to counties within 50km of an air pollution monitoring station. Column 4–6 replicate columns 1–3 using population weights. (*** p<0.01, ** p<0.05, * p<0.1.)

Table 4: County Orders and Pollution (PM2.5)

	(1)	(2)	(3)	(4)	(5)	(6)
	PM2.5	PM2.5	PM2.5	PM2.5	PM2.5	PM2.5
State Order	-2.833***	-2.819***	-2.816***			
	(0.690)	(0.699)	(0.686)			
County Order	-0.465	-0.473	-0.470	-2.928*	-2.875*	-2.898*
	(0.321)	(0.321)	(0.320)	(1.579)	(1.550)	(1.583)
COVID-19 Cases		-0.012			-0.474***	
		(0.013)			(0.044)	
COVID-19 Deaths			-1.084			-9.186
			(0.871)			(6.557)
Constant	11.759***	11.759***	11.757***	15.797***	15.796***	15.797***
	(2.249)	(2.254)	(2.265)	(2.700)	(2.714)	(2.704)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12930	12930	12930	9343	9343	9343
Counties	110	110	110	110	110	110

Notes: State orders and county orders significantly reduce PM2.5, but state orders override. Sample restricted to counties who implemented an order before their state. The dependent variable is average daily PM2.5 concentration at the county-level. For columns 1–3, the time period is January 1st, 2020 through April 30th, 2020. For columns 4–6, the time period is January 1st, 2020 through date of County Order to day before State Order (differs based on county). COVID-19 known cases and deaths per 10,000 people. Population 2019 population estimates. Standard errors reported in parentheses, clustered at the state-level. All columns include county and date fixed effects. Sample restricted to counties within 50km of an air pollution monitoring station. (*** p<0.01, ** p<0.05, * p<0.1.)

Table 5: State Orders and Social Distance

	(1) Ret. and Rec.	(2) Grocery	(3) Parks	(4) Transit	(5) Work	(6) Residential
State Order	-6.610***	-8.478***	-9.097**	-4.810***	-4.399***	2.063***
	(1.140)	(1.086)	(3.511)	(1.247)	(0.613)	(0.305)
Constant	6.140***	1.638***	17.943***	5.492***	0.843*	-0.916***
	(0.757)	(0.552)	(4.021)	(1.555)	(0.462)	(0.220)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	83670	82284	38891	49074	94794	61620
Counties	1334	1317	734	756	1393	1042

Notes: State orders significantly increase social distance. The dependent variable in column 1 is the change in the number and length of trips to non-essential retail and recreation areas compared to baseline. Column 2 is trips to grocery and pharmacies. Column 3 is visits to parks, such as local and national. Column 4 is visits to transit hubs, such as bus and railway stations. Column 5 is time spent at places of work. Column 6 is time spent in residence. The time period is January 1st, 2020 through April 30th, 2020. All columns include county and date fixed effects. Sample restricted to counties within 50km of an air pollution monitoring station. (*** p<0.01, ** p<0.05, * p<0.1.)

Table 6: Social Distancing Behaviors Reduce PM2.5

	(1) PM2.5	(2) PM2.5	(3) PM2.5	(4) PM2.5	(5) PM2.5	(6) PM2.5
Ret. and Rec.	0.027***					
	(0.004)					
Grocery		0.022***				
		(0.005)				
Parks			0.010***			
			(0.003)			
Transit				0.016***		
				(0.005)		
Work					0.035***	
					(0.007)	
Residential						-0.117***
						(0.023)
Constant	6.451***	6.570***	6.642***	6.676***	6.614***	6.725***
	(0.301)	(0.306)	(0.470)	(0.423)	(0.304)	(0.415)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91434	89484	41177	53120	104567	66504
Counties	1478	1455	784	819	1556	1133

Notes: Social distancing behaviors reduce local PM2.5 concentrations. The dependent variable is average daily PM2.5 concentration at the county-level. The time period is January 1st, 2020 through April 30th, 2020. Standard errors reported in parentheses, clustered at the state-level. All columns include county and date fixed effects. Sample restricted to counties within 50km of an air pollution monitoring station and with sufficient mobility data to ensure privacy. (*** p<0.01, ** p<0.05, * p<0.1.)

Table 7: State Orders Reduce PM2.5 Beyond Social Distancing

	(1) PM2.5	(2) PM2.5	(3) PM2.5	(4) PM2.5	(5) PM2.5
State Order	-1.076***	-0.909**	-0.945***	-0.929***	-0.840**
	(0.345)	(0.353)	(0.348)	(0.332)	(0.347)
Ret. and Rec.		0.025***			0.019***
		(0.004)			(0.004)
Grocery			0.015**		0.001
			(0.006)		(0.006)
Work				0.032***	0.021***
				(0.007)	(0.007)
Constant	6.766***	6.609***	6.739***	6.756***	6.638***
	(0.336)	(0.324)	(0.328)	(0.333)	(0.328)
Date FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Observations	79570	79570	79570	79570	79570
Counties	1296	1296	1296	1296	1296

Notes: State orders reduce PM2.5 levels even after accounting for reductions in social behaviors. The dependent variable is average daily PM2.5 concentration at the county-level. The time period is January 1st, 2020 through April 30th, 2020. Standard errors reported in parentheses, clustered at the state-level. All columns include county and date fixed effects. Sample restricted to counties within 50km of an air pollution monitoring station and with sufficient mobility data to ensure privacy. (*** $p<0.01$, ** $p<0.05$, * $p<0.1$.)

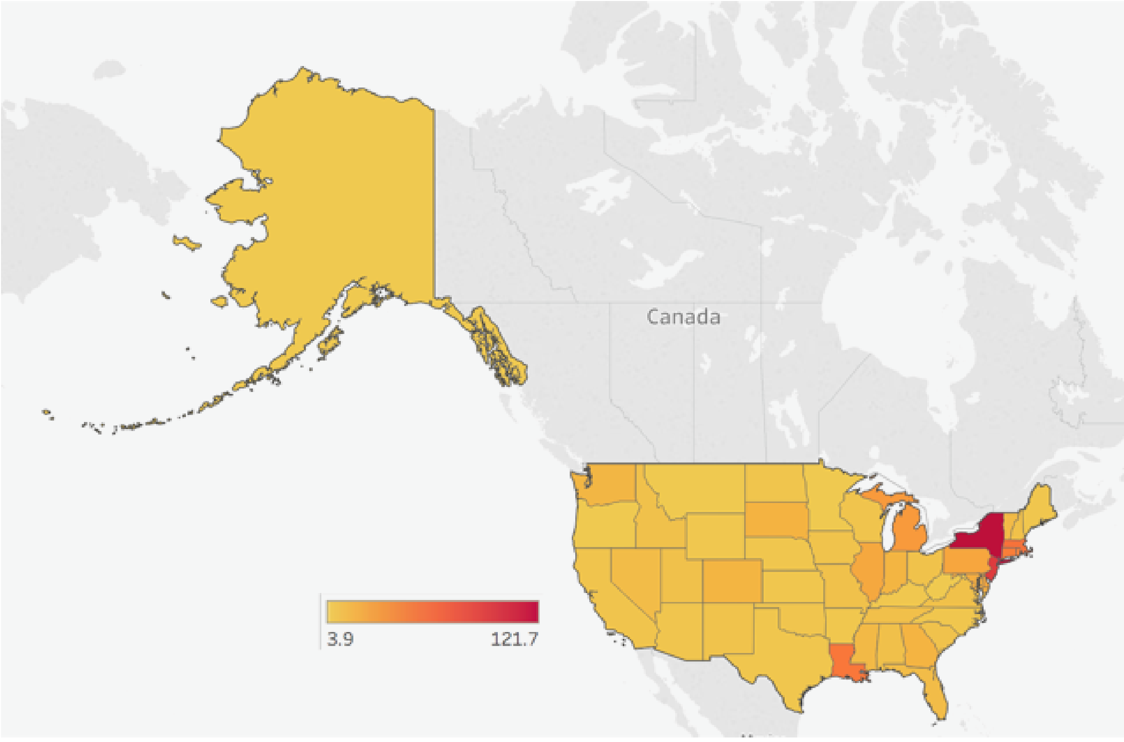
Table 8: State Orders Significantly Reduce Collisions

	(1) Collisions	(2) Collisions	(3) Collisions	(4) Collisions
State Order	0.404***	0.429***	0.405***	0.555***
	(0.012)	(0.013)	(0.012)	(0.018)
COVID-19 Cases		0.950***		
		(0.001)		
COVID-19 Deaths			0.521***	
			(0.010)	
Ret. and Rec.				1.009***
				(0.001)
Grocery				1.003***
				(0.001)
Work				1.029***
				(0.001)
Date FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Observations	15132	15132	15132	8008
Counties	310	310	310	224

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 sample includes all counties from the states of Alabama, Connecticut, Kentucky, Missouri, and Vermont. The time period is January 1st, 2020 through April 30th, 2020. COVID-19 known cases and deaths per 10,000 people. Population 2019 population estimates. Standard errors reported in parentheses. All columns include county and date fixed effects. (*** p<0.01, ** p<0.05, * p<0.1.)

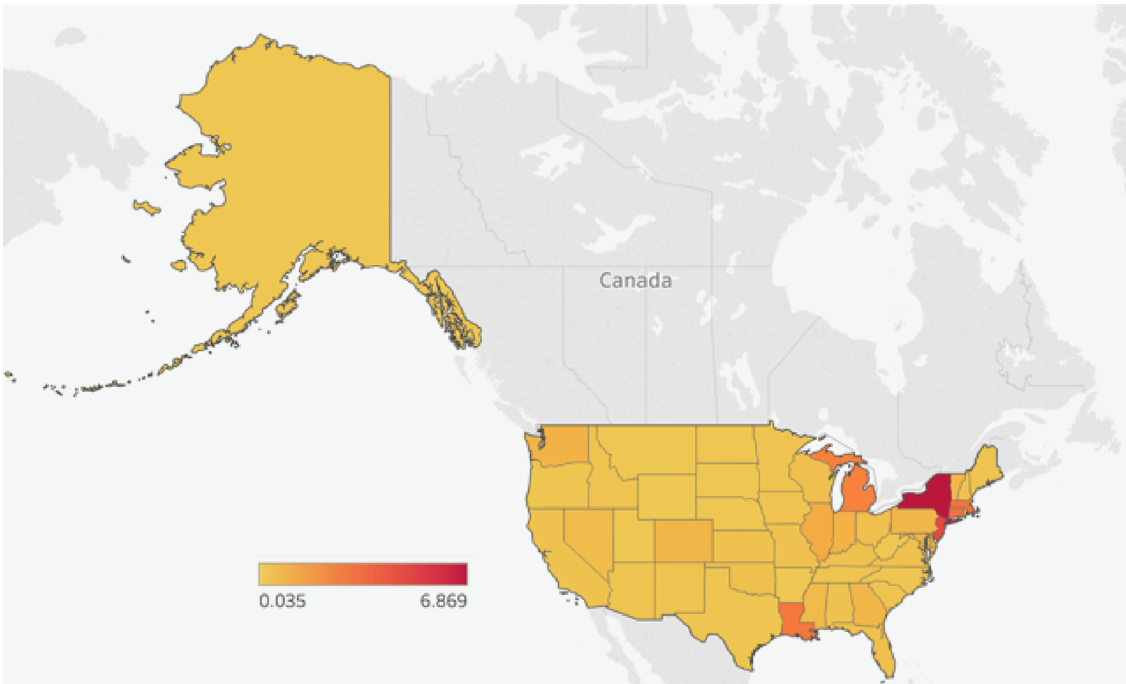
Appendix: NOT FOR PUBLICATION

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



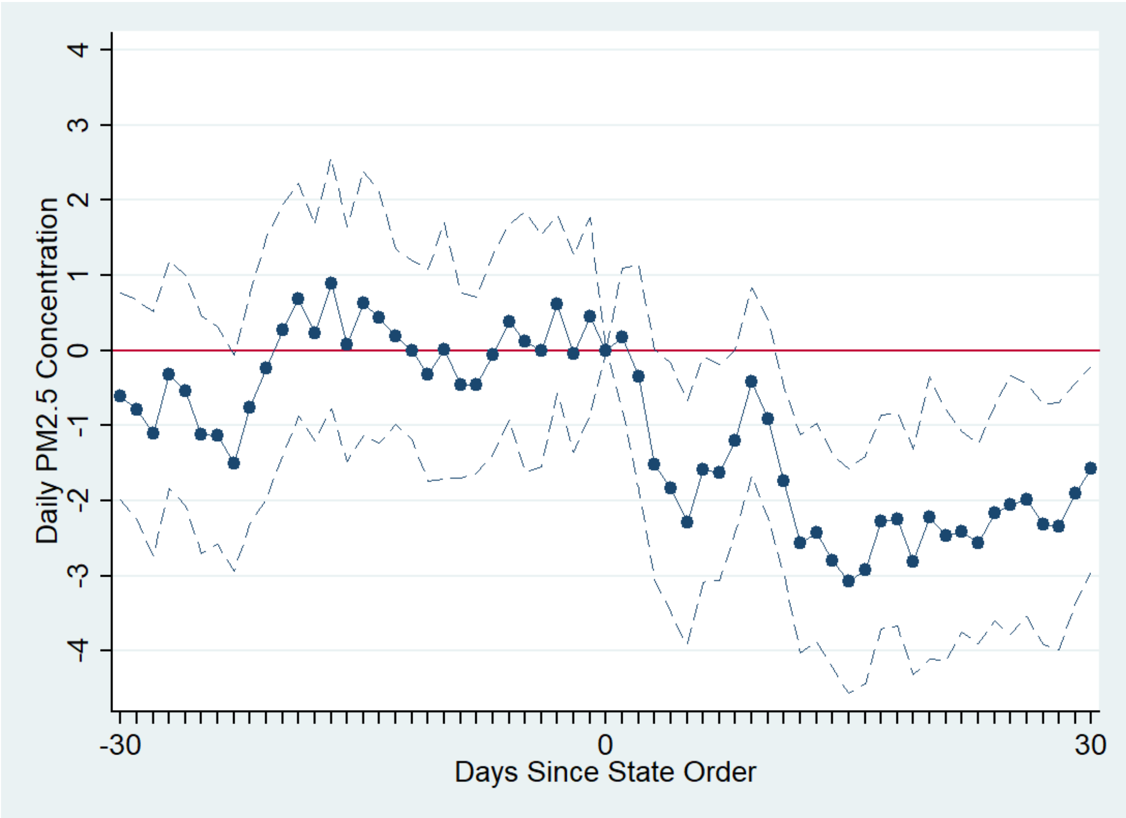
Notes: The map illustrates the cumulative number of (confirmed) COVID-19 cases per 10,000 inhabitants for each state as of April 18, 2020.

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



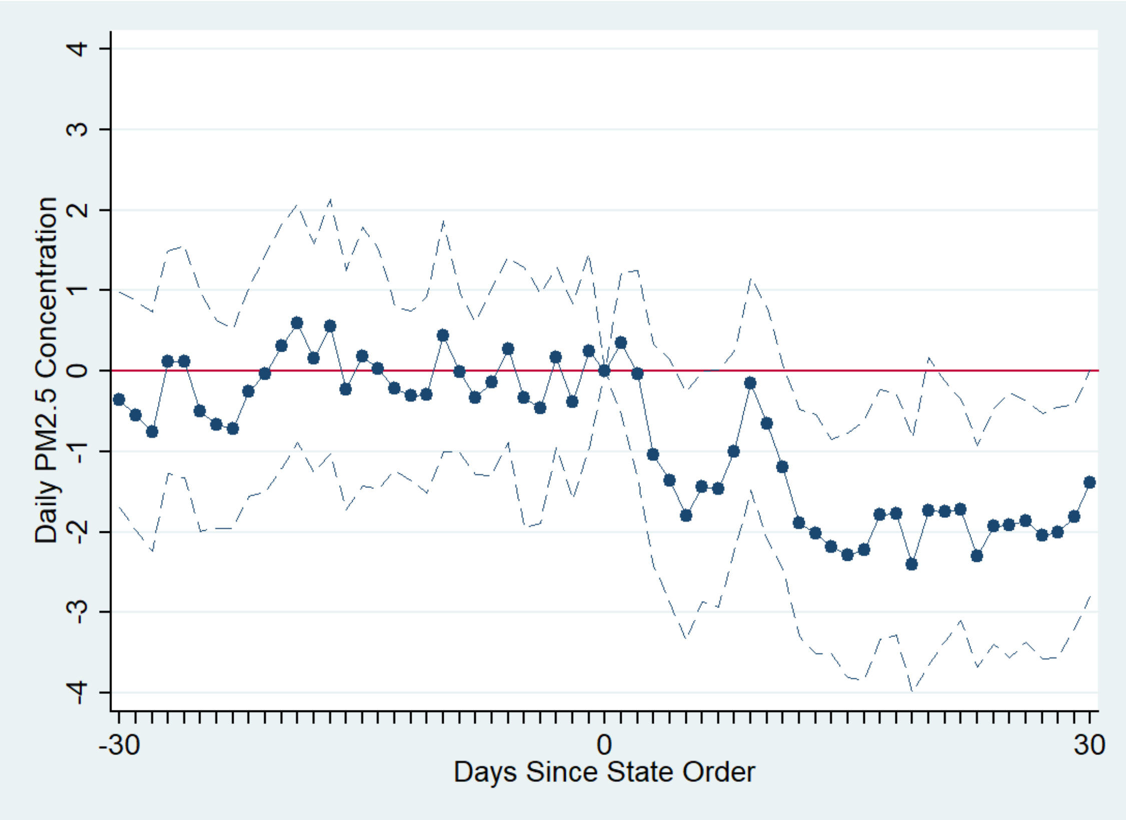
Notes: The map illustrates the number of COVID-19 deaths per 10,000 inhabitants for each state as of April 18, 2020.

Figure A3: PM2.5 Concentrations Over Time - Synthetic Control



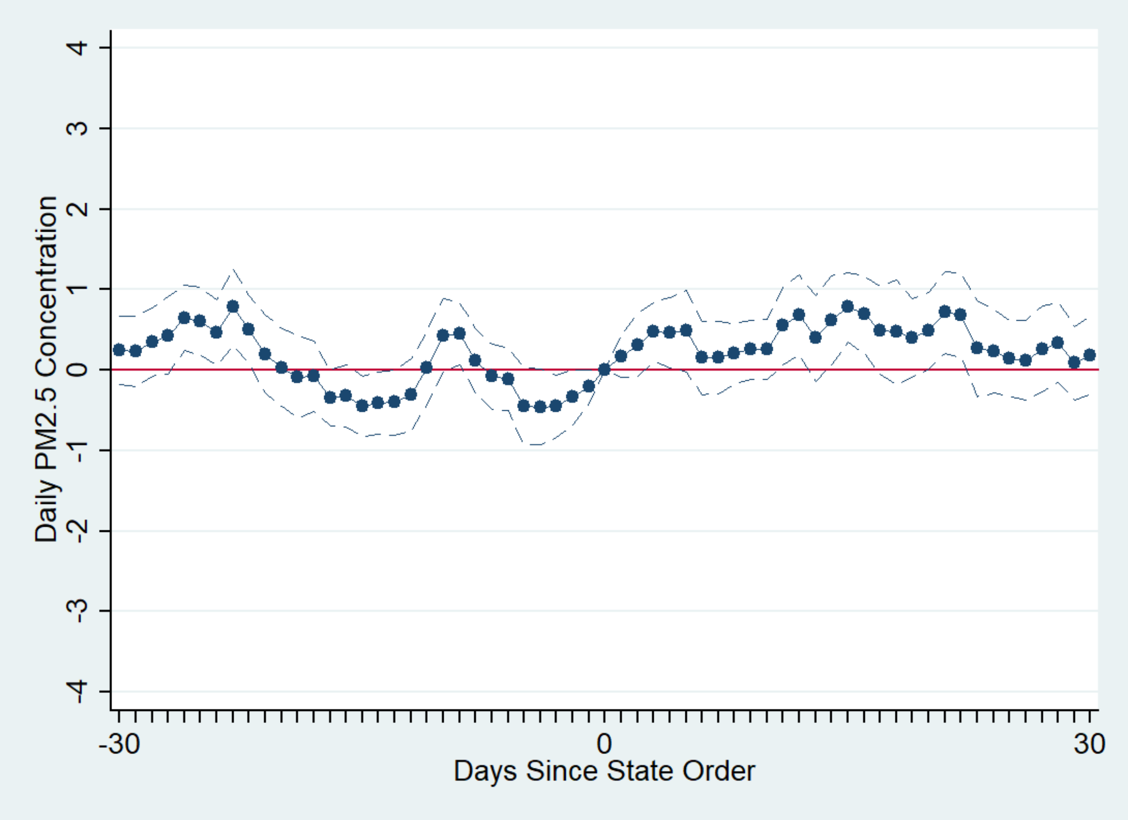
Notes: This figure presents the evolution of the difference between observed and synthetic control levels of PM2.5, before and after state orders. Plotted are regression coefficients of days since state order issued. Significance bands at the 95% level. County fixed effects model. Date fixed effects also included. Day-of-week fixed effects included for smoothing purposes - results are robust to their exclusion.

Figure A4: PM2.5 Concentrations Over Time - Observed



Notes: This figure presents the evolution of PM2.5 observed in the treated counties, before and after the 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. Day-of-week fixed effects included for smoothing purposes - results are robust to their exclusion.

Figure A5: PM2.5 Concentrations Over Time - Synthetic Control



Notes: This figure plots the evolution of PM2.5 in the synthetic control counties, our counterfactual, 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. Day-of-week fixed effects included for smoothing purposes - results are robust to their exclusion.

Table A1: State Orders and Pollution (PM2.5): Proactive and Reactive Counties

	(1) PM2.5	(2) PM2.5	(3) PM2.5	(4) PM2.5	(5) PM2.5	(6) PM2.5
State Order	-1.610***	-2.833***	-1.467***	-1.612***	-2.819***	-1.469***
	(0.440)	(0.690)	(0.435)	(0.440)	(0.699)	(0.435)
County Order		-0.465			-0.473	
		(0.321)			(0.321)	
COVID-19 Cases				-0.005	-0.012	-0.004
				(0.004)	(0.013)	(0.004)
Constant	6.780***	11.759***	6.380***	6.780***	11.759***	6.380***
	(0.827)	(2.249)	(0.727)	(0.827)	(2.254)	(0.726)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	162471	12930	149541	162471	12930	149541
Counties	1472	110	1362	1472	110	1362

Notes: State orders significantly reduce PM2.5. The dependent variable is average daily PM2.5 concentration at the county-level. Proactive counties (column 2 and 5) implemented their own orders. Reactive counties (column 3 and 6) had only state orders issued. The time period is January 1st, 2020 through April 30th, 2020. COVID-19 known cases and deaths per 10,000 people. Population 2019 population estimates. Standard errors reported in parentheses, clustered at the state-level. All columns include county and date fixed effects. Sample restricted to counties within 50km of an air pollution monitoring station. Column 2 is the subsample of counties that implemented their own county-level order. Column 3 is all other counties. (*** p<0.01, ** p<0.05, * p<0.1.)

Table A2: State Orders and Pollution (PM2.5 - Synthetic Control)

	(1) Diff.	(2) Diff.	(3) Diff.	(4) Diff.	(5) Diff.	(6) Diff.
State Order	-2.570***	-2.571***	-2.569***	-2.522***	-2.529***	-2.539***
	(0.404)	(0.404)	(0.404)	(0.381)	(0.382)	(0.386)
COVID-19 Cases		-0.002			-0.008	
		(0.004)			(0.005)	
COVID-19 Deaths			0.015			-0.077
			(0.065)			(0.055)
Constant	-0.924	-0.924	-0.924	0.613	0.613	0.613
	(0.873)	(0.873)	(0.873)	(1.308)	(1.315)	(1.312)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	162471	162471	162471	162471	162471	162471
Counties	1472	1472	1472	1472	1472	1472

Notes: State orders significantly reduce PM2.5. Synthetic control methods, by county. Donor counties required to have 2019 populations within 2000 of treated counties, and a pre-COVID PM2.5 history within 2 $\mu g/m^3$. The dependent variable is the *difference* between observed and counterfactual PM2.5 at the county-day level. The time period is January 1st, 2020 through April 30th, 2020. COVID-19 known cases and deaths per 10,000 people. Population 2019 population estimates. Standard errors reported in parentheses, clustered at the state-level. All columns include county and date fixed effects. Sample restricted to counties within 50km of an air pollution monitoring station. Column 4–6 replicate columns 1–3 using population weights. (*** p<0.01, ** p<0.05, * p<0.1.)

Table A3: State Orders and Average Distance Traveled

	(1) ADT	(2) ADT	(3) ADT	(4) Visits	(5) Visits	(6) Visits
State Order	-0.033***	-0.035***	-0.035***	-0.058***	-0.060***	-0.061***
	(0.008)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)
COVID-19 Cases		-0.001***			-0.001***	
		(0.000)			(0.000)	
COVID-19 Deaths			-0.010***			-0.012***
			(0.001)			(0.002)
Constant	0.018*	0.018**	0.018*	0.013	0.012	0.012
	(0.009)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33818	33818	33818	33818	33818	33818
Counties	654	654	654	654	654	654

Notes: The dependent variable is change in average distance traveled according to a pre-COVID baseline. In column 4,5, and 6, the dependent variable is percentage change in social visits according to a pre-COVID baseline. Sample restricted to counties with Unacast travel data. Column 2 is counties that implement their own county order prior to the state. Column 3 is that had the state impose an order. COVID-19 known cases and deaths per 10,000 people. Population 2019 population estimates. Standard errors reported in parentheses, clustered at the state-level. All columns include county and date fixed effects. Sample restricted to counties within 50km of an air pollution monitoring station. (*** p<0.01, ** p<0.05, * p<0.1.)

Table A4: State Orders Improve Air Quality Index (AQI)

	(1) AQI	(2) AQI	(3) AQI	(4) AQI	(5) AQI	(6) AQI
State Order	-5.981***	-5.989***	-5.992***	-9.071***	-9.109***	-9.200***
	(1.627)	(1.627)	(1.631)	(2.576)	(2.542)	(2.527)
COVID-19 Cases		-0.017			-0.038**	
		(0.017)			(0.018)	
COVID-19 Deaths			-0.152			-0.592***
			(0.270)			(0.173)
Constant	25.985***	25.985***	25.985***	37.423***	37.422***	37.422***
	(2.552)	(2.551)	(2.551)	(4.951)	(4.985)	(4.981)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	162471	162471	162471	162471	162471	162471
Counties	1472	1472	1472	1472	1472	1472

Notes: State orders significantly reduce Air Quality Index (higher measures indicate worse air quality; 0-50 is consider 'satisfactory'). The dependent variable is average daily AQI. The time period is January 1st, 2020 through April 30th, 20 COVID-19 known cases and deaths per 10,000 people. Population 2019 population estimates. Standard errors report in parentheses, clustered at the state-level. All columns include county and date fixed effects. Sample restricted to cou ties within 50km of an air pollution monitoring station. Column 4–6 replicate columns 1–3 using population weights. (* p<0.01, ** p<0.05, * p<0.1.)

Table A5: State Orders Reduce Air Quality Risk

	(1) AQI>50	(2) AQI>50	(3) AQI>50	(4) AQI>50	(5) AQI>50	(6) AQI>50
State Order	-0.099***	-0.099***	-0.099***	-0.173***	-0.173***	-0.174***
	(0.031)	(0.031)	(0.031)	(0.052)	(0.052)	(0.052)
COVID-19 Cases		-0.000			-0.000	
		(0.000)			(0.000)	
COVID-19 Deaths			-0.004			-0.007*
			(0.004)			(0.004)
Constant	0.110***	0.110***	0.110***	0.263***	0.263***	0.263***
	(0.038)	(0.038)	(0.038)	(0.077)	(0.077)	(0.077)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	162471	162471	162471	162471	162471	162471
Counties	1472	1472	1472	1472	1472	1472

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 is January 1st, 2020 through April 30th, 2020. COVID-19 known cases and deaths per 10,000 people. Population 2019 population estimates. Standard errors reported in parentheses, clustered at the state-level. All columns include county and date fixed effects. Sample restricted to counties within 50km of an air pollution monitoring station. Column 4–6 replicate columns 1–3 using population weights. (*** p<0.01, ** p<0.05, * p<0.1.)

Table A6: State Orders and Pollution - Differences-in-differences (PM2.5)

	(1) PM2.5	(2) PM2.5	(3) PM2.5	(4) PM2.5	(5) PM2.5	(6) PM2.5
State Order	-1.197***	-1.197***	-1.191***	-1.193***	-2.105***	-2.083***
	(0.357)	(0.357)	(0.356)	(0.356)	(0.714)	(0.721)
COVID-19 Cases			-0.005			-0.009*
			(0.004)			(0.005)
COVID-19 Deaths				-0.037		
				(0.066)		
Constant	6.662***	6.662***	6.662***	6.662***	10.661***	10.660***
	(0.745)	(0.745)	(0.745)	(0.745)	(1.790)	(1.797)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	181331	181331	181331	181331	181331	181331
Counties	1651	1651	1651	1651	1651	1651

Notes: All states (including those who never implemented a state order). State orders significantly reduce PM2.5. The
able is average daily PM2.5 concentration at the county-level. The time period is January 1st, 2020 through April 30th,
known cases and deaths per 10,000 people. Population 2019 population estimates. Standard errors reported in parenth
the state-level. All columns include county and date fixed effects. Sample restricted to counties within 50km of an air poll
station. Column 4–6 replicate columns 1–3 using population weights. (*** p<0.01, ** p<0.05, * p<0.1.)

Table A7: State Orders and Pollution Heterogeneity - Differences-in-diff

	Urban (1)	Rural (2)	Majority Trump (3)	Minority Trump (4)	Above Median 65+ (5)	Below Median 65+ (6)
State Order	-1.781***	-1.322***	-1.374***	-2.066***	-1.207***	-1.883***
	(0.511)	(0.394)	(0.402)	(0.491)	(0.429)	(0.490)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	89890	72581	116128	46343	63254	99217
Counties	783	689	1073	399	579	893

Notes: All states (including those who never implemented a state order). The dependent variable is average daily PM2 is January 1st, 2020 through April 30th, 2020. COVID-19 known cases and deaths per 10,000 people. Standard error All columns include date fixed effects. Sample restricted to counties within 50km of an air pollution monitoring statio and rural counties, respectively. Columns 2–4 are for counties in which a majority voters voted for President Trump. below median share of population aged 65 and over, respectively. Columns 7–8 are for counties in states with above and remotely, respectively. (*** p<0.01, ** p<0.05, * p<0.1.)

Table A8: Kentucky Fatal Collisions Decrease

	(1) Fatal Collisions	(2) Fatal Collisions	(3) Fatal Collisions	(4) Fatal Collisions
State Order	0.323***	0.657*	0.501**	0.469***
	(0.074)	(0.154)	(0.171)	(0.131)
Collisions		1.020***	1.020***	1.021***
		(0.002)	(0.002)	(0.002)
COVID-19 Cases			1.022	
			(0.020)	
COVID-19 Deaths				1.523**
				(0.251)
Date FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Observations	4546	4546	4546	4546
Counties	64	64	64	64

Notes: Kentucky state order significantly reduced fatal collision rate. Poisson model with fixed effects. The dependen variable is count of fatal traffic collisions at the county-level. Coefficients are incidence rate-ratios, wherein a value be low one indicates a decrease in the dependent variable and a value above indicates an increase. The sample includes a counties from the state of Kentucky. The time period is January 1st, 2020 through April 30th, 2020. COVID-19 know cases and deaths per 10,000 people. Population 2019 population estimates. Standard errors reported in parentheses. A columns include county and date fixed effects. (*** p<0.01, ** p<0.05, * p<0.1.)