Appendix to Are We #Stayinghome to Flatten the Curve?

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A Data Discussion

A.1 Location Data

Each device on a given date was assigned to the state where that device spent the longest time on that day. This assignment rule captures short-term travel across state borders and allows for temporary reassignment when travel takes a resident out of state for a longer period of time. It also allows for people to move their place of residence during the observation period and be reassigned to the new state. The pre-COVID-19 period is defined as the four weeks prior to and inclusive of March 8, 2020. The COVID-19 period therefore begins on March 9. Our mobility data sample period begins February 24, 2020 and ends April 29, 2020.

A.1.1 Average Distance Traveled

To capture the change in overall travel activity, we employ a measure of the change in average distance traveled per day during the COVID-19 period. To the extent that individuals in a given state are engaging in social distancing, working from home, or adhering to stay-at-home mandates, we expect average travel distances to fall relative to pre-COVID-19 norms. Travel activity is measured as the overall distance a device traveled in a day and is therefore independent of home location. The average distance traveled per day in a state is then given by the average across all devices assigned to that state on a given day:

$$\overline{ADT}_{it} = \frac{1}{N_{it}} \sum_{j=1}^{N_{it}} Dist_{jit}$$

Where $Dist_{jit}$ is the distance traveled by individual j in region i on date t and N_{it} is the number of mobile devices assigned to region i on date t. To obtain a relative measure of travel distance changes, a baseline is constructed. For each day of the week, the weekday-specific baseline is computed as the average distance traveled for that weekday in the pre-COVID-19 period:

$$\overline{ADT}^{B}_{iw} = \frac{1}{N_{iw}} \sum_{\ell \in L^B_w} \sum_{j=1}^{N_{it}} Dist_{ji\ell}$$

where L^B_w is the set of dates for day of week w in the pre-COVID-19 period and N_{iw} is the total number of users observed in region i on the four dates for weekday w during this period. As the pre-COVID-19 period contains four dates for each weekday, $\overline{ADT}^{B}_{iw}$ is an average of all travel activity over those four days.

Then, for each COVID-19 date, the change in average distance traveled ($A\dot{D}T$) in a given region is constructed as the percentage point change in travel activity relative to that day of week's baseline:

$$A\dot{D}T_{it} = \left(\frac{\overline{ADT}_{it}}{\overline{ADT}^{B}_{iw}} - 1 \right) \times 100 \tag{1}$$

A value of $A\dot{D}T_{it} = 0$ indicates that the average distance traveled for individuals in state i on date t was identical to the pre-COVID-19 distance for that day of the week. A value of -7 conveys that, on average, devices assigned to the state traveled an average distance 7 percentage points shorter than during the pre-COVID-19 baseline. This approach allows us to account for differences in travel potential by day of week, making sure our comparison accurately reflects the average conditions for that day of the week prior to behavior and policy changes due to COVID-19.

A.1.2 Non-Essential Visits

Our utilized measure of the change in visits to non-essential businesses ($\dot{NEV}$) offers a similar comparison targeted at travel to the types of businesses most heavily impacted by stay-at-home mandates. As travel to essential businesses (i.e. supermarkets and pharmacies) is not restricted by state stay-at-home mandates, the measure focuses only on visitations to points of interest likely affected by non-essential business closures. Businesses likely to be deemed "non-essential" include department stores, spas and salons, fitness facilities, event spaces, and many others; non-essential businesses are defined according to group definitions in both the Unacast SDK and the OpenStreetMaps POI's to improve accuracy (see Table 1 for a complete list of included business types). Visitations to these businesses are then extracted from visitation data available in the Unacast SDK. The metric $\dot{NEV}$ is constructed similarly to $\dot{ADT}$, replacing the average distance traveled per day with the average visitations to non-essential businesses:

$$N\dot{E}V_{it} = \left(\frac{\overline{NEV}_{it}}{\overline{NEV}^{B}_{iw}} - 1 \right) \times 100 \tag{2}$$

Where the baseline is again constructed as the average for a given weekday in the pre-COVID-19 period for a given state. A value of $N\dot{E}V_{it} = 2$ indicates a two percentage point increase in visitations to non-essential businesses relative to baseline norms for that weekday in a given state.

A.1.3 Measurement Concerns

Our utilized measure of changes in non-essential visits captures observed travel behavior to the types of businesses likely affected by state stay-at-home mandates and reflects both closures and modified business practices. While some categories of businesses were closed with near uniformity across state policies (i.e. casinos), others included exceptions for certain subgroups or under particular types of activity. For example, the particular restrictions across states on whether restaurants were required to suspend operation entirely or could continue offering orders for drive-through, curbside pickup, or delivery varied highly, with many states heavily restricting but still allowing home improvement stores to operate. In this manner, visitations to non-essential visits will never hit zero. While we do not expect to perfectly capture the particulars of each states' policies, this measure is intended to provide a proxy that can speak to changes in observed behavior.

Further, the measure's definition and our empirical approaches are able to control for many of the suspected sources of bias. The comparison to the pre-COVID-19 baseline for a given day of the week normalizes the value relative to visitation levels at a time not yet affected by COVID-19 concerns. In addition, our difference-and-differences and weighted event study are identified using residual variation remaining after partially off the averages for a given state, day of week, and date or state-specific cubic time trends. This eliminates measurement error concerns arising from differences in classification errors state to state, as our approach controls for any fixed distribution of business types in a state. General variation in classification error across states would introduce a source of attenuation bias that would drive our estimated treatment effects toward zero. One remaining scenario in which our estimates would be biased would be the case in which systematic variation existed over time in classification error that was correlated with travel to these stores and with the adoption of stay-at-home policies (or in the weighted event study case with time elapsed post-implementation). If our sample included an extensive period during which many states were modifying or eliminating their stay-at-home mandates, then we would be concerned with falsely attributing visitation changes due to mandate easings to their implementations. However, this would serve to introduce upward bias to our ATT estimates, leading to underestimation of the reductions in visitations due to stay-at-home mandates.

A.1.4 Human Encounter Rate

The Unacast metric for human encounters follows that of [13] and is defined as

$$ENC_{it} = \frac{\sum_{j=1}^{N_{it}} Encounters_{jit} \; / \; Land\ Area_i}{E\bar{N}C^{B}}$$

Where $Encounters$ is the sum of unique encounters across all devices N_{it} assigned to state i on date t and $Land\ Area$ measures the square kilometers of land area for the state. An encounter is counted when two users from the same geographic area are observed within a 50 meter radius circle of each other for no more than 60

Table 1: Non-Essential Business Type

Category	Business Type
Unacast POIs	Restaurant (multiple kinds), Department Store, Clothing (multiple kinds), Footwear, Discount Stores, Jewelry, Computers + Consumer Electronics, Gifts, Seasonal, Books, Office Supplies, Hair, Cosmetics + Beauty Supplies, Gyms + Fitness Facilities, Communications, New/Used Car Dealers, Hotels, Used Products, "Crafts, Toys, and Hobbies", Travel, "Spa, Massage, + Aesthetics", Sports + Recreation, Weight Loss, Furnishings, Home + Housewares, Home Improvement +Building Supplies, "Printing, Copying + Publishing", Theatres, Music, Amusement, Furnishing Rentals, Shared Offices + Coworking, Car Wash, Cannabis Retail, Flowers
OpenStreetMap "amenity" POIs	bar, pub, cafe, restaurant, theatre, nightclub, cinema, casino
OpenStreetMap "leisure" POIs	bowling_alley, fitness_centre, cafe, restaurant, theatre, nightclub
OpenStreetMap "shop" POIs	department_store, mall, clothes, shoes, doityourself, furniture, sports

minutes. In this way the numerator provides a normalized measure of encounters that is reflective of typical patterns for both rural and urban environments.

Encounters per square kilometer are then divided by the baseline encounter rate before subtracting off one. In contrast to the changes in average distance traveled and non-essential visits, Unacast uses "the national average encounter density during the 4 weeks that immediately precede COVID-19 outbreak (February 10th - March 8th)" (Ngo 2020). An absolute baseline is used here to better reflect the potential for infection in more densely populated areas. As a result, ENC_{it} is interpreted as the percentage point change in the encounter rate relative to the national pre-COVID-19 average. An encounter rate equal to that of the national baseline rate results in a value of $ENC_{it} = 0$, while a value of $ENC_{it} = -12$ indicates a 12 percentage point reduction in the encounter rate for state i on date t relative to the "business-as-usual" national baseline. To convert the unique human encounter rate to a relative measure, we divide the Unacast-provided encounter rate for a given state and day by that state's average for the observed portion of the baseline period (February 24 to March 8):

$$E\dot{N}C_{it} = \left(\frac{\overline{ENC}_{it}}{\overline{ENC}_i^B} - 1 \right) \times 100 \tag{3}$$

In this way our employed encounter rate normalizes the encounter rate ratio relative to the baseline for a given state, reflecting the extent to which residents of a given state are reducing their encounter rate relative to that states' pre-COVID-19 level.

A.2 Health Data

We obtain information on hospitalizations and deaths from COVID-19 by state from the COVID Tracking Project [8]. Published values are obtained directly from the respective public health authorities, supplemented with additions from press conferences or trusted news sources. Controversy exists about how to measure deaths and whether all those that are truly COVID 19-related are being captured in existing counts, or only those for which the patient has been tested, which would result in the new daily death rate data we use to be under reported, but these are the most up to date health data available. In terms of the hospitalization data, there are 12 states and Washington D.C. that do not report a consistent time series of hospitalizations due to COVID-19, including three of the first four adopters: California, Delaware, Illinois, Louisiana, Michigan, Missouri, North Carolina, Nebraska, New Jersey, Nevada, Texas, and Washington., resulting in missing values for the hospitalization analysis.

To investigate the time patterns of health outcomes, we start by breaking up the average death rate by day separately for two groups of states: those that are mandate states and the eight states that are not. In Figure 2, we see that average death rates increase more for states that did implement mandates than for those states that did not and that the patterns for hospitalization rates are noisier, as shown in the bottom panel of this

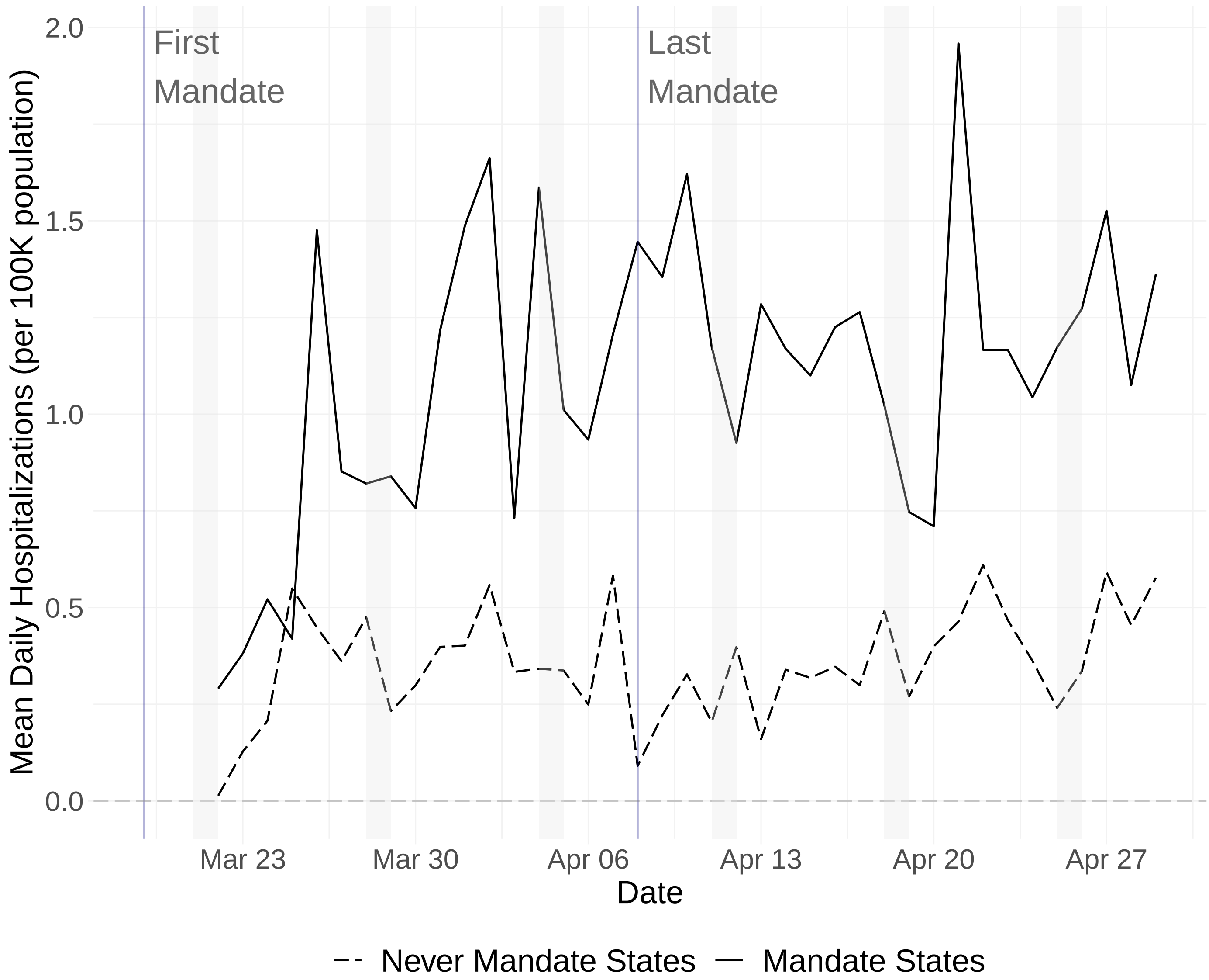


Figure 1: Source: Health Data source COVID-19 Tracking Project. Mandate states are all states that adopted at some point a stay at home mandate. The eight non-mandate states are Arkansas, Iowa, Oklahoma, Nebraska, North Dakota, South Dakota, Utah, and Wyoming. The vertical lines indicates March 19 and April 8, the dates of the first and last statewide stay-at-home mandates.

figure.

We provide here additional patterns for the evolution of average death and hospitalization rates by day across states. We split states into two groups and report the averages separately for states that exhibit larger than median and lower than median drops in mobility, non essential visits, and encounter rates. Looking at the time patterns for states that experience the largest reductions in mobility and distinguish from the average death rates for the states that experience the lowest mobility reductions (lower than the median drop), as measured by daily changes in average distance traveled, we show in Figure 3 that the increase in death rates is different for those states that have the smallest reductions in mobility. The hospitalization evolution is noisier as show in the bottom panel. The patterns are similar for the break down by reductions in non essential visits in Figure 4 and in encounter rates as shown in both panels in Figure 5.

A.3 Health Data Quality

While all states report both the change and running total of deaths, reporting of hospitalizations is less consistent and often incomplete. Tables 2 and 3 summarize the data quality and coverage for deaths and hospitalizations across all states and Washington D.C. for states reporting and not reporting hospitalization data, respectively. As of May 2, 37 states report at least two days of hospitalization data while 13 and Washington D.C. report no hospitalization data. While state consistently report between 30 and 60 days of death data as both daily changes and running totals, hospitalization data is much more sparse and reported

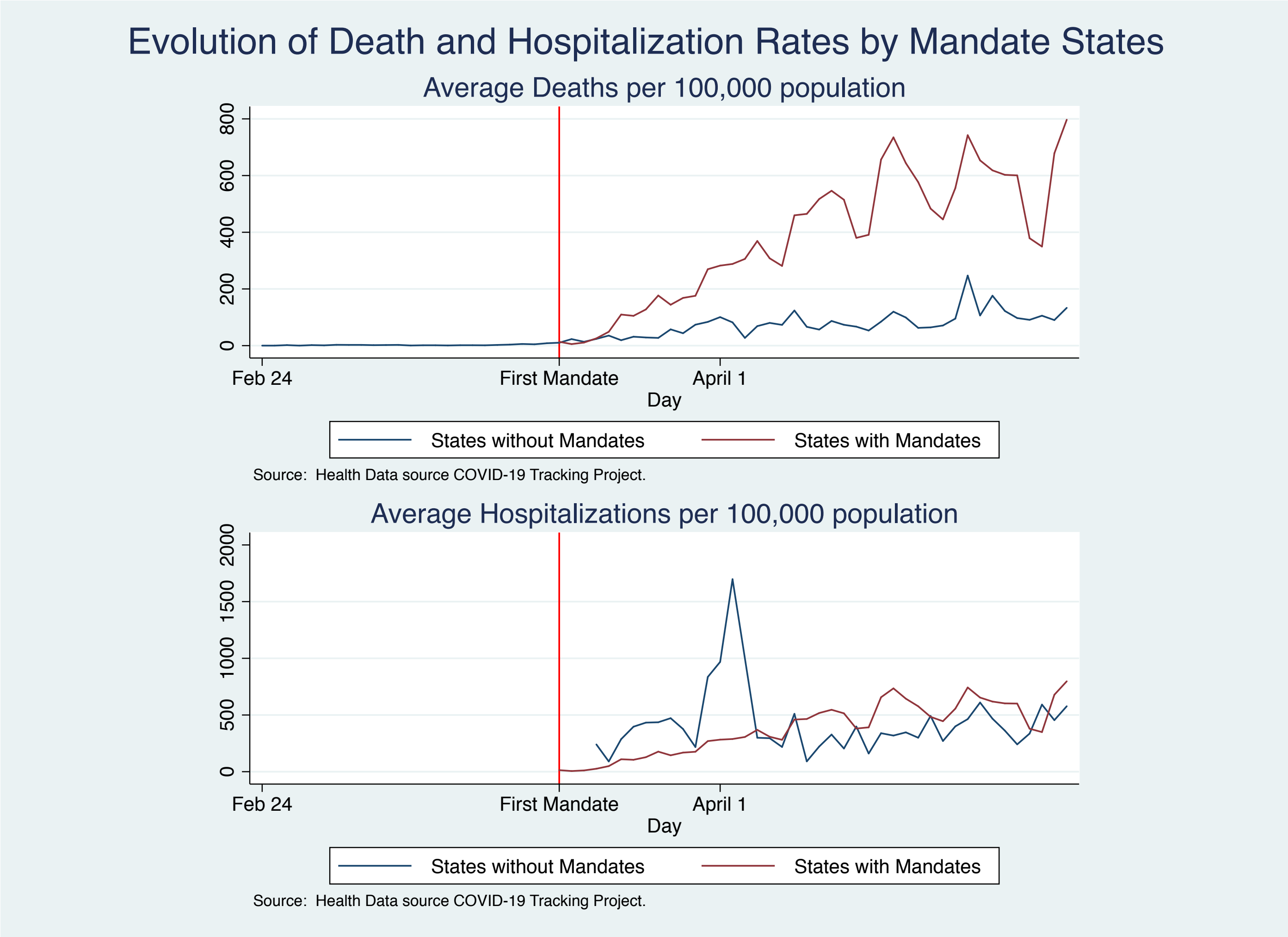


Figure 2: Source: Health Data source COVID-19 Tracking Project. Mandate states are all states that adopted at some point a stay at home mandate. The eight non-mandate states are Arkansas, Iowa, Oklahoma, Nebraska, North Dakota, South Dakota, Utah, and Wyoming. The red vertical line indicates March 19, the date the first state policy was implemented in California.

in different ways by different states. Alaska and Connecticut report hospitalization as both the daily change and running total, while the remaining 35 states only report the cumulative number of hospitalization by date. Hospitalization data coverage ranges from a minimum of 2 days (Connecticut) to a maximum of 42 days (Colorado, Florida, Massachusetts, New York, North Dakota, Ohio, and Oklahoma). As we utilize the daily change per 100 million residents as outcomes of interest in our main analyses, we convert all hospitalization data provided as sums only to the daily change before dividing by 100 million population.

To evaluate overall data quality by state, CVT assigns a quality grade. This letter grade is assigned by analyzing 16 different factors across 5 categories. These factors include reporting characteristics ("Is the state's official COVID-19 website the best source that exists for that state's consistent, reliably updated data," and "Does the state format its COVID-19 data in a machine-readable way?"), testing data completeness ("Is the state reporting the total number of positive test results," "Is the state reporting the total number of negative test results," and "Is the state reporting the total number of tests conducted?"), reporting on patient outcomes ("Is the state reporting how many patients are hospitalized with COVID-19," "Is the state reporting how many patients with COVID-19 are being treated in ICUs," "Is the state reporting how many patients with COVID-19 are on ventilators," and "Is the state reporting how many patients have recovered from COVID-19?"), demographic reporting ("Is reported data broken down by patients' pre-existing conditions," "Does the state break down reported COVID-19 cases into racial categories," "Does the state break down reported COVID-19 cases into ethnic categories," "Does the state break down reported COVID-19 deaths into racial categories," and "Does the state break down reported COVID-19 deaths into ethnic categories"), along with whether the state reports hospital capacity and report data in the form of line lists [8]. As the grades combine reporting for testing with mortality and morbidity and demographic reporting, these grades are best interpreted as a measure of the completeness of reporting.

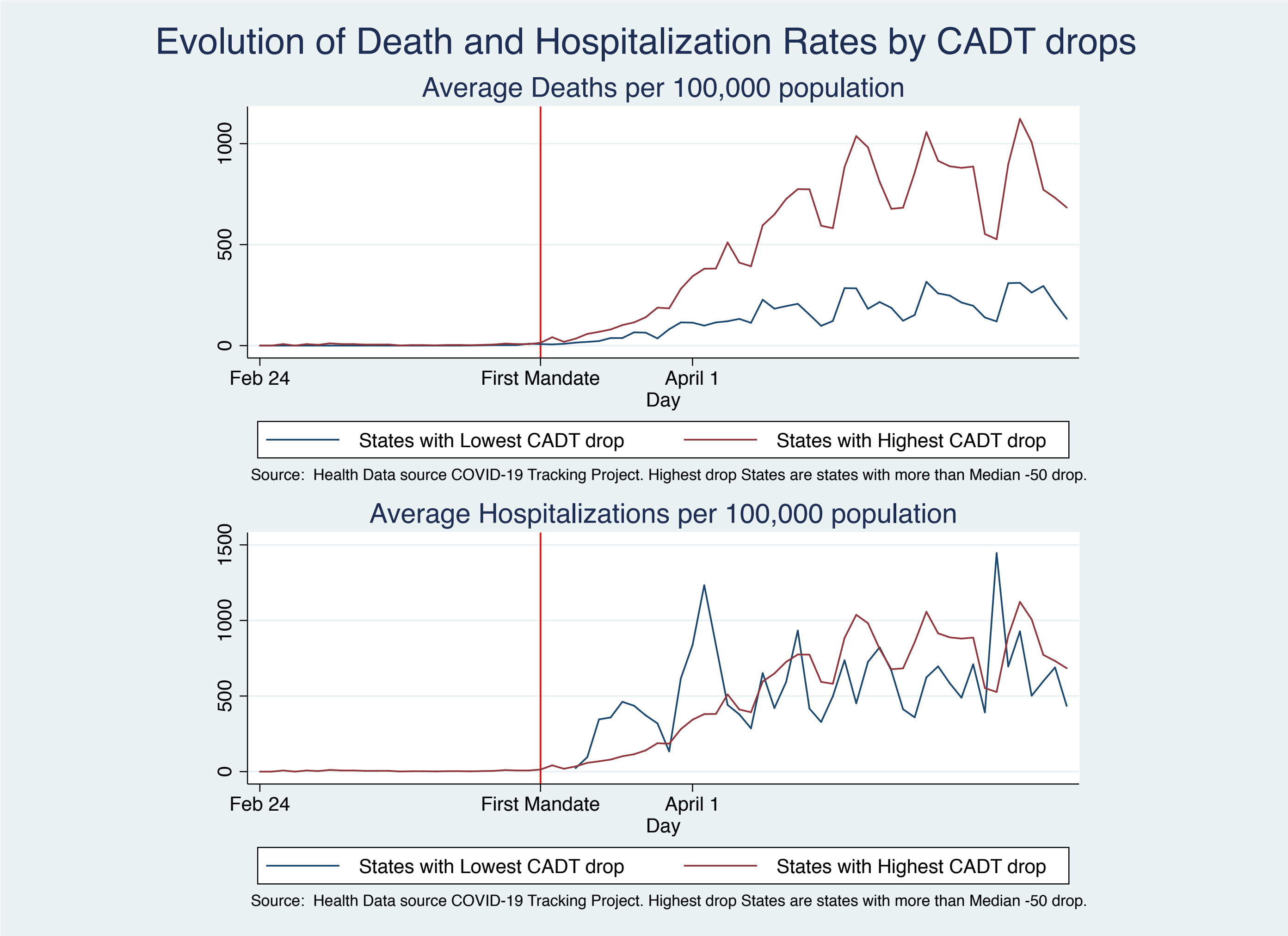


Figure 3: Source: Health Data source COVID-19 Tracking Project. The evolution is broken up by two groups of states, those with drops in the change in average distance traveled ($A\dot{D}T$) larger than the median drop by state, and those with drops lower than the median (where the median drop is -30.9%). The states with higher than median drop in CADT are: AK, CA, CO, CT, DE, FL, HI, IL, MA, MD, ME, MI, MN, NH, NJ, NV, NY, OH, PA, RI, VT, WA, WI. The red vertical line indicates March 19, the date the first state policy was implemented in California.

Mortality and morbidity data obtained from CVT correlate strongly with other sources of COVID-19 health data. We chose CVT as our main source of health outcome data as they were found to balance transparency with coverage and stood as the most complete source of hospitalization data. To provide evidence for the insensitivity of our health findings to our choice of data source, we next compare our utilized mortality data to that from two other major sources. In Table 4 we present the correlations of COVID-19 mortality data from three sources: CVT, the New York Times' "Coronavirus (Covid-19) Data in the United States" project [12], and the COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University [11].

Table 5 provides rankings of states on counts of health outcomes and intensities per million. The gray rows reflect the first four states to adopt statewide stay-at-home mandates, with the table reporting the 15 states with the highest overall incidences of mortality and morbidity from COVID-19.

Table 2: Health Data Quality, States Reporting Hospitalization Data

	State /District	Quality Grade	Days of Death Data	Form of Death Data	Days of Hosp. Data	Form of Hosp. Data
1	Alabama	B	48	Change and Sum	28	Sum only
2	Alaska	C	57	Change and Sum	33	Change and Sum
3	Arizona	A+	50	Change and Sum	8	Sum only
4	Arkansas	B	41	Change and Sum	27	Sum only
5	Colorado	B	49	Change and Sum	42	Sum only
6	Connecticut	B	44	Change and Sum	2	Change and Sum
7	Florida	C	52	Change and Sum	42	Sum only
8	Georgia	A+	50	Change and Sum	38	Sum only
9	Hawaii	B	31	Change and Sum	39	Sum only
10	Idaho	C	41	Change and Sum	35	Sum only
11	Iowa	A	38	Change and Sum	16	Sum only
12	Kansas	A	49	Change and Sum	36	Sum only
13	Kentucky	A	47	Change and Sum	22	Sum only
14	Maine	B	36	Change and Sum	33	Sum only
15	Maryland	A	44	Change and Sum	37	Sum only
16	Massachusetts	A	45	Change and Sum	42	Sum only
17	Minnesota	A	42	Change and Sum	41	Sum only
18	Mississippi	B	43	Change and Sum	41	Sum only
19	Montana	C	35	Change and Sum	37	Sum only
20	New Hampshire	C	39	Change and Sum	39	Sum only
21	New Mexico	C	38	Change and Sum	18	Sum only
22	New York	B	48	Change and Sum	42	Sum only
23	North Dakota	C	50	Change and Sum	42	Sum only
24	Ohio	B	43	Change and Sum	42	Sum only
25	Oklahoma	A	44	Change and Sum	42	Sum only
26	Oregon	A	45	Change and Sum	41	Sum only
27	Pennsylvania	B	45	Change and Sum	11	Sum only
28	Rhode Island	A+	34	Change and Sum	19	Sum only
29	South Carolina	B	47	Change and Sum	38	Sum only
30	South Dakota	C	45	Change and Sum	32	Sum only
31	Tennessee	B	40	Change and Sum	38	Sum only
32	Utah	C	48	Change and Sum	32	Sum only
33	Vermont	C	43	Change and Sum	13	Sum only
34	Virginia	B	48	Change and Sum	38	Sum only
35	West Virginia	C	48	Change and Sum	17	Sum only
36	Wisconsin	A+	43	Change and Sum	32	Sum only
37	Wyoming	C	36	Change and Sum	36	Sum only

This table summarizes the quality and coverage of health data obtained from the Covid Tracking Project (CVT) for states reporting hospitalization data. *Quality Grade* reports the letter grade assigned by CVT representing the overall data quality based on 16 categories (see the Data Appendix discussion for these categories). *Sum* indicates that the State health authority only reports the cumulative total, while *Change and Sum* indicates they report both the daily change and running total.

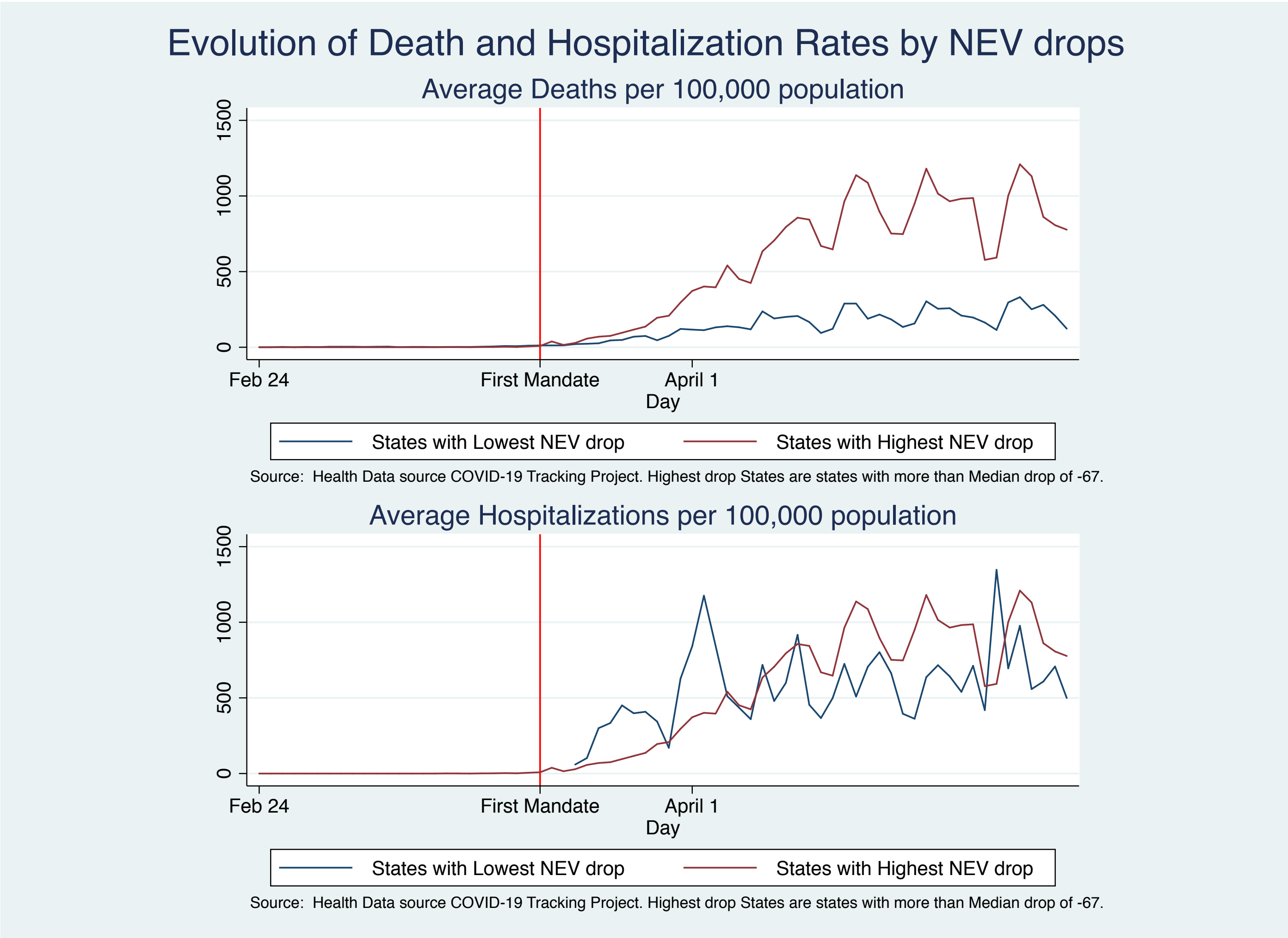


Figure 4: Source: Health Data source COVID-19 Tracking Project. The evolution is broken up by two groups of states: those with drops in the change in Non-Essential Visits (NEV) larger than the median drop by state, and those with drops lower than the median (where the median drop is -67%). The states with higher than median drop in NEV are CA, CO, CT, DE, HI, IA, IL, MA, MD, MI, MN, MT, NH, NJ, NV, NY, PA, RI, VT, WI. The red vertical line indicates March 19, the date the first state policy was implemented in California.

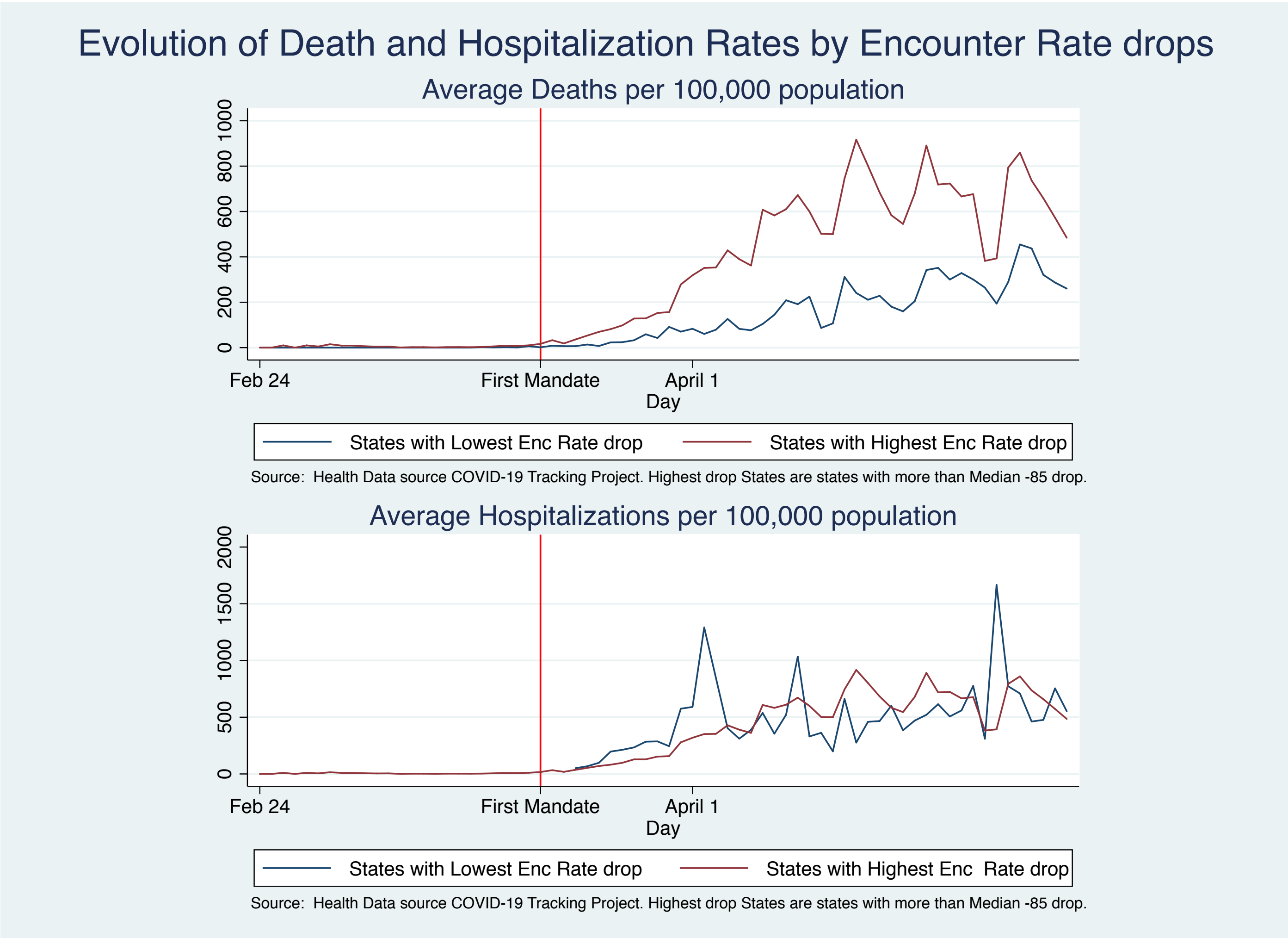


Figure 5: Source: Health Data source COVID-19 Tracking Project. The evolution is broken up by two groups of states, those with drops in the change in the rate of unique human encounters ($E\dot{N}D$) larger than the median drop by state, and those with drops lower than the median (where the median drop is -71.6%). The states with drops smaller than the median are AK, AZ, DC, DE, IA, ID, IN, KS, MO, MT, NC, ND, NE, NM, OH, SC, SD, UT, VA, WV, WY. The red vertical line indicates March 19, the date the first state policy was implemented in California.

Table 3: Health Data Quality, States Not Reporting Hospitalization Data

	State /District	Quality Grade	Days of Death Data	Form of Death Data	Days of Hosp. Data	Form of Hosp. Data
1	California	B	51	Change and Sum	0	NA
2	Delaware	B	44	Change and Sum	0	NA
3	Illinois	A	46	Change and Sum	0	NA
4	Indiana	A+	49	Change and Sum	0	NA
5	Louisiana	B	48	Change and Sum	0	NA
6	Michigan	A+	44	Change and Sum	0	NA
7	Missouri	A	49	Change and Sum	0	NA
8	Nebraska	D	44	Change and Sum	0	NA
90	Nevada	D	47	Change and Sum	0	NA
10	New Jersey	A+	52	Change and Sum	0	NA
11	North Carolina	B	47	Change and Sum	0	NA
12	Texas	B	46	Change and Sum	0	NA
13	Washington	B	66	Change and Sum	0	NA
14	Washington D.C.	B	44	Change and Sum	0	NA

This table summarizes the quality and coverage of health data obtained from the Covid Tracking Project (CVT) for states not reporting hospitalization data. *CVT Quality Grade* reports the letter grade assigned by CVT representing the overall data quality based on 16 categories (see the Data Appendix discussion for these categories). *Sum* indicates that the State health authority only reports the cumulative total, while *Change and Sum* indicates they report both the daily change and running total.

Table 4: Correlation of COVID-19 Deaths by State and Sources

State	Cor(CVT, NYT)	Cor(CVT, JH)	Cor(JH, NYT)	Cor(CVT, NYT)	Cor(CVT, JH)	Cor(JH, NYT)
AK	0.9993	0.9999	0.9991	0.9958	1	0.9958
AL	0.9999	0.9998	0.9998	0.9993	0.9992	0.9994
AR	0.9997	0.9991	0.9991	0.9989	0.9983	0.9995
AZ	1	1	1	0.9999	0.9987	0.9986
CA	0.9994	0.9995	0.9999	0.9994	0.9995	0.9999
CO	0.9993	0.999	0.9992	0.9973	0.9971	0.9991
CT	0.9997	0.9998	0.9999	0.9998	0.9999	1
DC	1	1	1	1	1	1
DE	0.9993	0.9993	1	0.9991	0.9991	0.9999
FL	0.9998	0.9998	0.9999	0.9996	0.9996	0.9998
GA	0.9996	0.9999	0.9995	0.9994	0.9998	0.9993
HI	0.9988	0.9974	0.9968	0.987	0.9924	0.9915
IA	1	1	1	0.9997	0.9999	0.9995
ID	0.9968	0.9995	0.9977	0.9973	0.9996	0.9972
IL	1	1	1	1	1	1
IN	1	1	1	0.9988	0.9991	0.9982
KS	0.9998	0.9995	0.9998	0.9995	0.9987	0.9994
KY	0.9991	0.9992	0.9991	0.999	0.9989	0.9992
LA	1	1	1	1	0.9997	0.9997
MA	0.9996	0.9994	0.9999	0.9899	0.9861	0.9992
MD	1	1	1	1	0.9931	0.9931
ME	1	0.9996	0.9996	1	0.9994	0.9994
MI	0.998	0.998	1	1	0.9997	0.9997
MN	1	0.9999	0.9999	1	0.9999	0.9999
MO	1	0.9997	0.9997	0.9968	0.9973	0.9978
MS	1	1	1	1	1	1
MT	0.999	0.9995	0.9987	0.995	0.9965	0.9939
NC	1	0.9999	0.9999	0.9995	0.999	0.9989
ND	1	0.9997	0.9998	0.999	0.9949	0.9947
NE	0.9986	0.9983	0.9995	0.9958	0.999	0.9955
NH	0.9991	0.9984	0.9985	0.9964	0.9974	0.9964
NJ	1	1	1	1	0.9999	0.9999
NM	0.9993	0.9988	0.9991	0.9983	0.9981	0.9978
NV	0.9998	0.9996	0.9997	0.9989	0.9993	0.9985
NY	1	1	1	1	0.9975	0.9975
OH	0.9997	0.9997	1	1	0.9999	0.9999
OK	1	0.9999	0.9999	1	1	1
OR	0.9998	0.9995	0.9995	0.9989	0.999	0.9991
PA	0.9998	0.9998	1	0.9954	0.997	0.9994
RI	1	0.9993	0.9993	0.997	0.9965	0.9989
SC	0.9994	0.9994	0.9999	0.9975	0.9972	0.9992
SD	1	1	1	0.9991	0.9991	1
TN	0.9998	0.9992	0.9992	0.9992	0.9987	0.9987
TX	0.9998	0.9998	0.9999	0.9996	0.9996	0.9997
UT	1	0.9999	0.9999	1	0.9979	0.9979
VA	1	1	1	1	0.9998	0.9998
VT	0.9999	0.9999	1	0.9991	0.9997	0.9989
WA	0.9989	0.9987	0.9996	0.9971	0.9968	0.9998
WI	1	0.9999	0.9999	0.9997	0.9996	0.9998
WV	0.9995	0.9997	0.9993	0.9983	0.9982	0.9983
WY	0.9839	0.9711	0.9774	1	0.9746	0.9746

This table reports the correlations in death counts by state from the Covid Tracking Project (CVT), The New York Times (NYT), and the COVID-19 Data Repository at Johns Hopkins University (JH).

Table 5: State Ranks on Mortality and Morbidity from COVID-19

State	SAH Date	1st Case	1st Death	Tests Count	Tests /M	Cases Count	Cases /M	Hosp. /M	Deaths /M
WA	3-23	1	1	1	1	3	2	1	1
NY	3-22	8	6	2	5	2	3	5	5
CA	3-19	3	2	3	21	4	26	11	11
MA	3-24*	5	28	7	15	6	4	13	13
OR	3-23	6	12	17	16	21	21	4	4
FL	4-03	9	3	14	36	7	18	8	8
NJ	3-21	13	4	22	42	5	7	6	6
IL	3-21	2	17	8	23	8	14	20	20
LA	3-23	37	11	20	29	9	5	2	2
MI	3-24	36	22	4	12	1	1	33	33
SD	NA	40	5	26	6	46	28	3	3
ME	4-02	41	45	12	3	27	9	31	31
VT	3-25	28	25	19	4	42	11	48	48
NM	3-24	39	40	6	2	35	27	40	40
AZ	3-31	4	32	46	49	38	49	23	23

This table presents the timing of state stay-at-home mandates and rankings on health outcome counts and intensities per million residents for the pre-mandate period of February 24 to March 18. A ranking of 6 indicates the state was the sixth earliest to report its first case or death, or had the sixth highest count or level per million residents over the period. *Massachusetts Governor Charlie Baker issued a stay-at-home "advisory" on March 24 that fell short of a formal order.

A.4 Stay-at-Home Mandate Timing

Table 6: Stay-at-Home Policy Adoption Timing

State /District	SAH Mandate Effective	Coded First Effective Date	State /District	SAH Mandate Effective	Coded First Effective Date
California	March 19	March 19	Kansas	March 30, 12:01am	March 30
Illinois	March 21, 5pm	March 22	North Carolina	March 30, 5pm	March 31
New Jersey	March 21, 9pm	March 22	Maryland	March 30, 8pm	March 31
New York	March 22, 8pm	March 23	Virginia	March 30	March 30
Ohio	March 23, 11:59pm	March 24	Tennessee	March 31, 11:59pm	April 1
Louisiana	March 23, 5pm	March 24	Arizona	March 31, 5pm	April 1
Connecticut	March 23, 8pm	March 24	Washington D.C.	April 1, 12:01am	April 1
Oregon	March 23	March 23	Pennsylvania	April 1, 8pm	April 2
Washington	March 23	March 23	Nevada	April 1	April 1
Idaho	March 24, 1:30pm	March 24	Maine	April 2, 12:01am	April 2
Indiana	March 24, 11:59pm	March 25	Texas	April 2, 12:01am	April 2
Michigan	March 24, 12:01am	March 24	Florida	April 3, 12:01am	April 3
Massachusetts*	March 24, 12pm	March 24	Mississippi	April 3, 5pm	April 4
Delaware	March 24, 8am	March 24	Georgia	April 3	April 3
New Mexico	March 24, 8am	March 24	Alabama	April 4, 5pm	April 5
West Virginia	March 24, 8pm	March 25	Missouri	April 6, 12:01am	April 6
Hawaii	March 25, 12:01am	March 25	South Carolina	April 7, 5pm	April 8
Vermont	March 25, 5pm	March 26	Arkansas		
Wisconsin	March 25, 8am	March 25	Iowa		
Colorado	March 26, 6am	March 26	Nebraska		
Kentucky	March 26, 8pm	March 27	North Dakota		
Minnesota	March 27, 11:59pm	March 28	Oklahoma		
New Hampshire	March 27, 11:59pm	March 28	South Dakota		
Montana	March 28, 12:01am	March 28	Utah		
Alaska	March 28, 5pm	March 29	Wyoming		
Rhode Island	March 28	March 28			

This table reports the date and time at which various states adopted their stay-at-home mandates. *Coded First Effective Date* is equal to the next date when the SAH mandate was adopted at 5pm or later and is equal to the adoption date otherwise. *Massachusetts Governor Charlie Baker issued a stay-at-home "advisory" on March 24 that fell short of a formal order.

B Decomposition of the Difference-in-Differences Mandate Effects

To better understand how our stay-at-home mandate effect estimates are weighted combinations of all possible two-by-two ATT estimates, we decompose the treatment effects for the staggered difference-in-differences estimators into their component two-by-two DD effects following [9] .

Table 7: Components of Goodman-Bacon (2018) two-by-two DD Estimators

Group	Description
$k = 1$	California ($t_1^* =$ March 19)
$k = 2$	Illinois and New Jersey ($t_2^* =$ March 22)
$k = 3$	New York ($t_3^* =$ March 23)
U	States that adopt later or never adopt SAH mandates (46)
Period	**Description**
$Post(1)$	March 19 - April 29
$Post(2)$	March 22 - April 29
$Post(3)$	March 23 - April 29
$Pre(1)$	February 24 - March 18
$Pre(2)$	February 24 - March 21
$Pre(3)$	February 24 - March 22
$Mid(1,2)$	March 19 - March 21
$Mid(1,3)$	March 19 - March 22
$Mid(2,3)$	March 22
$\bar{Y}_h^{Post(j)}$	Mean of Y for group h during the period after group j's adoption: $\left(\sum_{t=t_j^*}^{T} Y_{ht}\right)/(T+1-t_j^*)$
$\bar{Y}_h^{Pre(j)}$	Mean of Y for group h during the period before group j's adoption: $\left(\sum_{t=1}^{t_j^*} Y_{ht}\right)/t_j^*$
$\bar{Y}_h^{Mid(j)}$	$\bar{Y}$ for group h during the period between groups h and j's adoption: $\left(\sum_{t=t_h^*}^{t_j^*-1} Y_{ht}\right)/(t_j^* - t_h^*)$

This table reports components of the two-by-two difference-in-differences estimators resulting from the Goodman-Bacon (2018) decomposition. Treatment is defined as equal to one when each of the first 4 adopters of stay-at-home mandates has their mandate in place, and is equal to zero otherwise. The estimated model includes state and date fixed effects.

B.1 Decomposition for Travel Activity and Social Distancing

The following Figures 6, 7, and 8 replicate the Goodman-Bacon decomposition for analyses identifying the ATT using variation in stay-at-home mandate adoption for all states that ever adopt such a mandate. Tables 8, 9, and 10 report the number, weight, and average ATT for each of the three comparison types. As there is much more variation timing when comparing across all 43 adopters, the staggered DD ATT can now be decomposed into 324 unique two-by-two estimators. Across all three travel behavior variables, considerably more weight is now placed on within-treatment group comparisons. Weight of 0.22 is placed on the 153 unique DD estimates for comparisons of earlier versus later treated states while 0.21 of the weight falls on later versus earlier treated comparisons. The remaining 0.56 weight is placed on pairwise comparisons of each of the 18 treatment timing cohorts to the eight states that never adopt statewide stay-at-home mandates. The greater heterogeneity in policy timing and characteristics across states is clear in the greater variation of simple DD estimates for each type of comparison. However, while some positive comparisons are obtained, they represent a small fraction of the total estimates. For example, only 16 positive ATT estimates are obtained across all 54 Treated vs Untreated comparisons for the three outcomes. Further, the mean ATT for each type of comparison is negative for all groups and all outcomes, with estimates narrowed to each comparison group spanning a maximum of -2.4 and a minimum of -6.2. Taken together, results of the decomposition provide evidence that our overall travel activity ATT estimates are not dependent on a single outlier or a single type of comparison, and instead reflect a weighted average of three types of overwhelmingly negative comparisons for both early adopters and all statewide stay-at-home mandates.

B.1.1 ADT

Figure 6: Composite Two-by-Two ATT Estimators for All Stay-at-Home Mandates, Average Distance Traveled

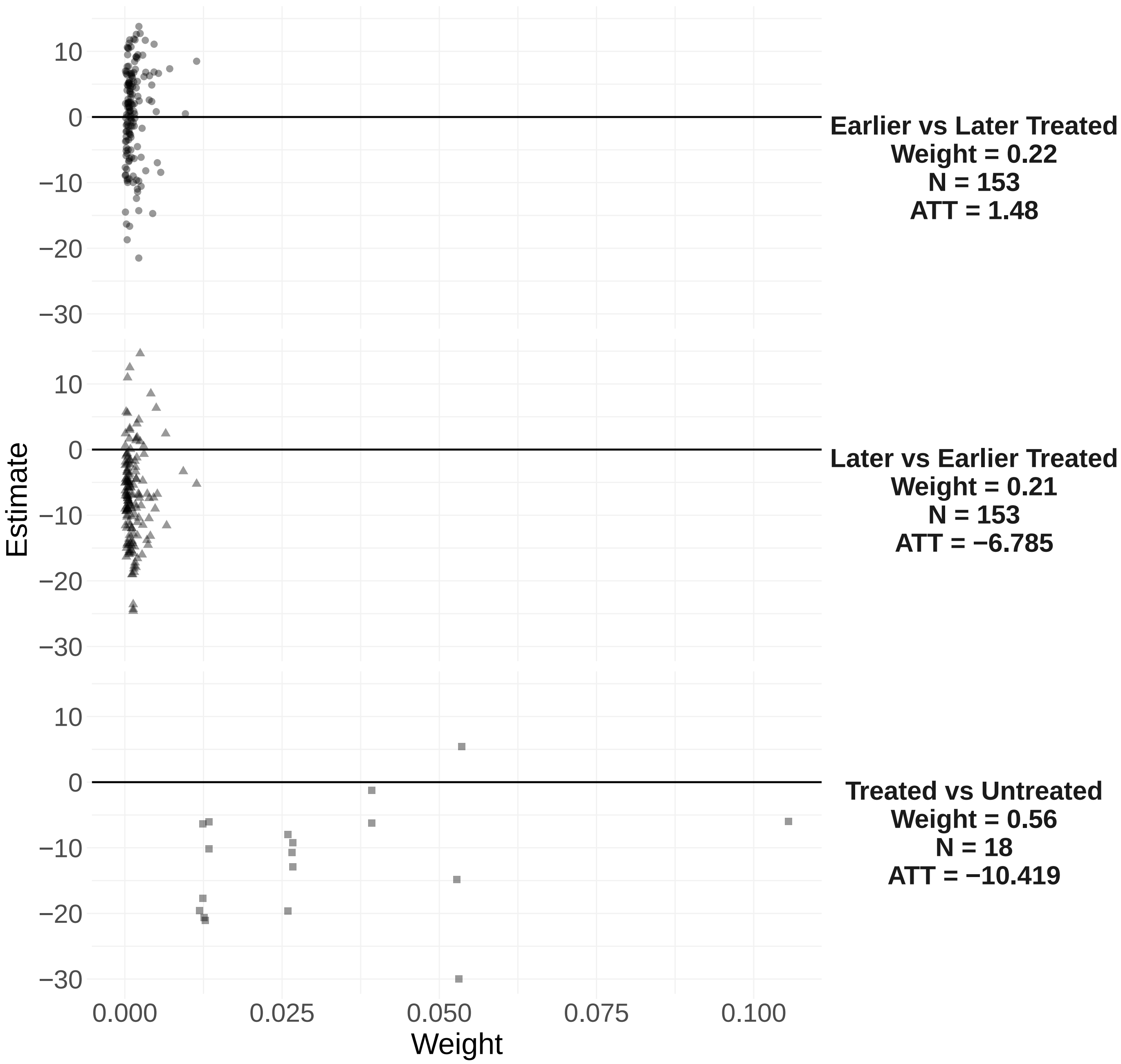


Table 8: Goodman-Bacon Decomposition of Stay-at-Home Mandate Effect for Changes in Average Daily Distance Traveled

Comparison	# Estimates	Mean ATT	Comparison Weight
Earlier vs Later Treated	153	0.514077552869069	0.222993516414937
Later vs Earlier Treated	153	-7.18842914949705	0.212906914901793
Treated vs Untreated	18	-11.9339617967808	0.56409956868327

This table reports the two-by-two Difference-in-Difference estimates obtained through the Goodman-Bacon (2019) decomposition of the staggered Difference-in-Differences estimate. All outcomes are residualized of timing cohort pre-trends.

Figure 7: Composite Two-by-Two ATT Estimators for All Stay-at-Home Mandates, Non-Essential Visits

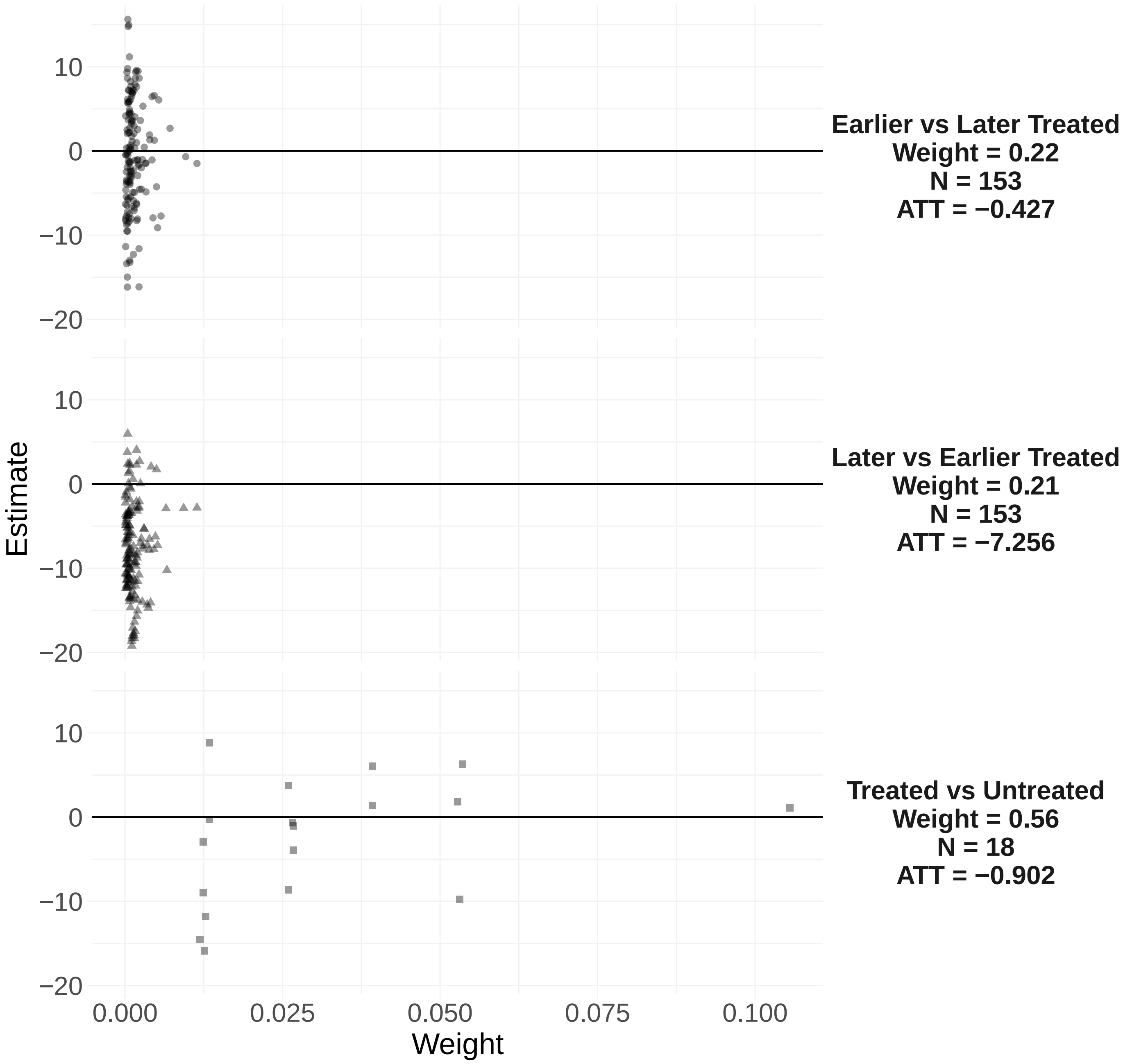


Table 9: Goodman-Bacon Decomposition of Stay-at-Home Mandate Effect for Changes in Visits to Non-essential Businesses

Comparison	# Estimates	Mean ATT	Comparison Weight
Earlier vs Later Treated	153	-0.547783573649073	0.222993516414937
Later vs Earlier Treated	153	-7.60179686402067	0.212906914901793
Treated vs Untreated	18	-2.73031895747824	0.56409956868327

This table reports the two-by-two Difference-in-Difference estimates obtained through the Goodman-Bacon (2019) decomposition of the staggered Difference-in-Differences estimate. All outcomes are residualized of timing cohort pre-trends.

Figure 8: Composite Two-by-Two ATT Estimators for All Stay-at-Home Mandates, Human Encounter Rate

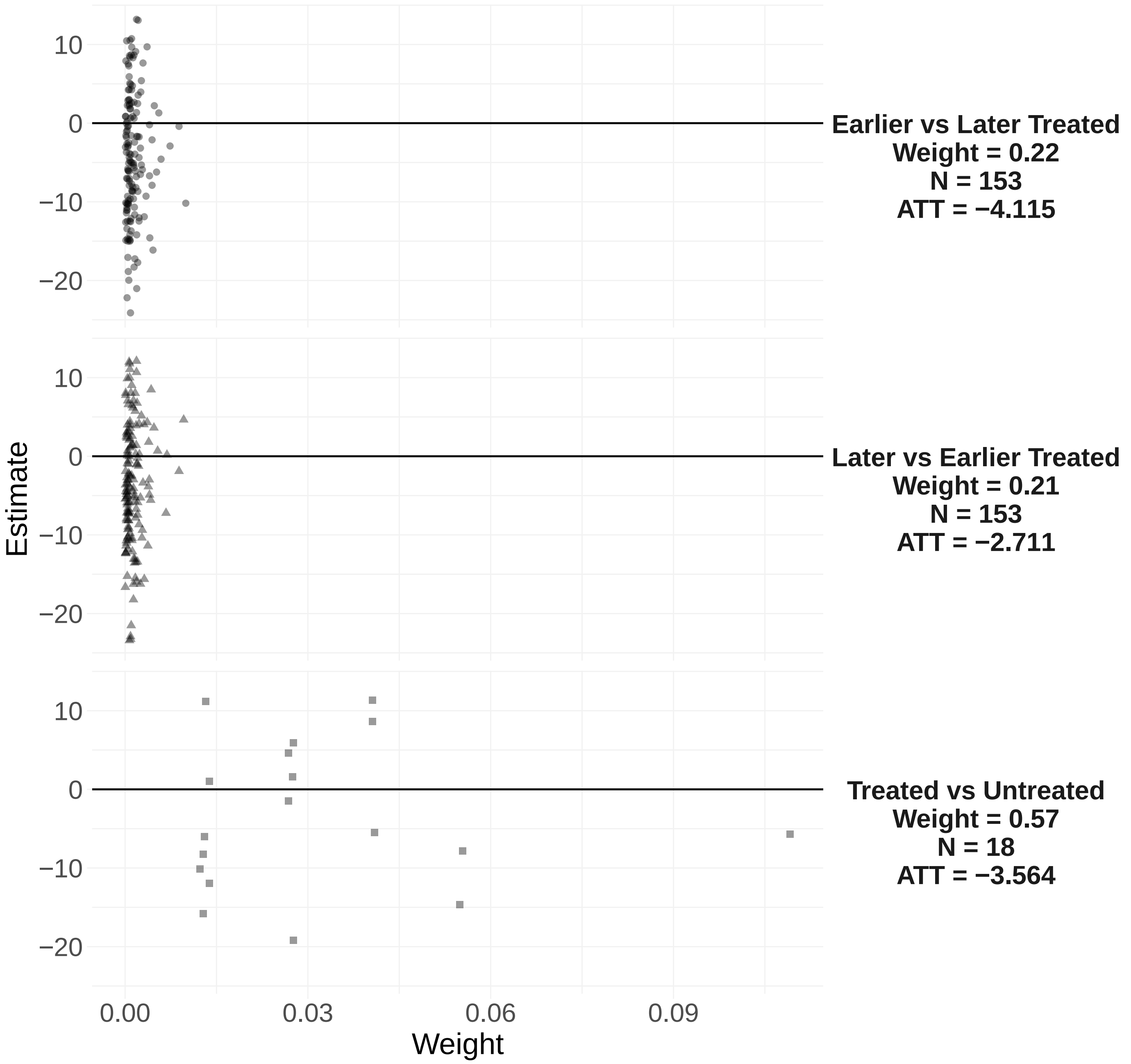


Table 10: Goodman-Bacon Decomposition of Stay-at-Home Mandate Effect for Changes in Human Encounters

Comparison	# Estimates	Mean ATT	Comparison Weight
Earlier vs Later Treated	153	-4.29488460262696	0.220057481496554
Later vs Earlier Treated	153	-3.50548306172766	0.210214411069003
Treated vs Untreated	18	-3.45551146953968	0.569728107434443

This table reports the two-by-two Difference-in-Difference estimates obtained through the Goodman-Bacon (2019) decomposition of the staggered Difference-in-Differences estimate. All outcomes are residualized of timing cohort pre-trends.

B.2 Decomposition for COVID-19 Mortality

Figure 15 and Table 11 replicate the Goodman-Bacon decomposition for analyses of COVID-19 mortality using the balanced version of the two week pre-treatment sample (pre-periods trimmed to March 5 for all states).

Figure 9: Composite Two-by-Two ATT Estimators for All Stay-at-Home Mandates, Deaths per 100,000 Population

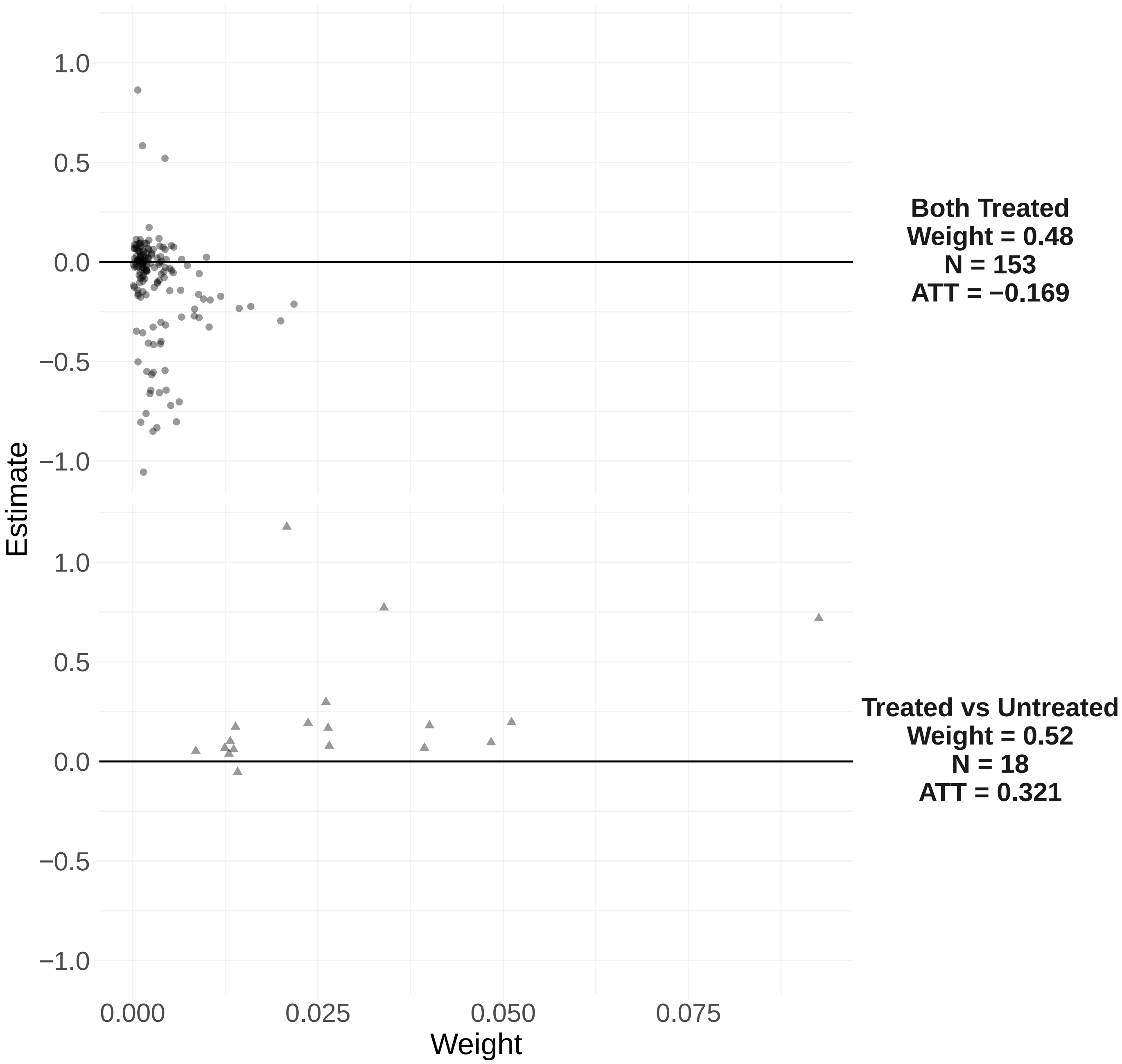


Table 11

Type	Count	Weight	ATT Estimate
Treated vs Untreated	18	0.517778663775543	0.166152580782899
Both Treated	153	0.482221336224457	-0.0814998988723053

This table reports the weights and ATT estimates obtained through the Goodman-Bacon (2019) decomposition for each comparison type. Dependent variable is death rates per 100,000 population residualized of pre-treatment period cohort trends (following Goodman-Bacon 2018). Controls are pre-period average changes in all three mobility measrues.

C Travel Analyses: Robustness

The following tables and figures report results from alternate specifications of the difference-in-differences and event study models for mobility behavior and social distancing impacts of stay-at-home mandates.

C.1 Difference-in-Differences Models

The following table presents difference-in-differences estimates for the level mobility changes (note residualized of cohort pre-trends).

Table 12: Statewide Stay-at-Home Mandates, Travel Activity, and Social Distancing

	$\dot{ADT}$	$\dot{NEV}$	$\dot{ENC}$	$\dot{ADT}$	$\dot{NEV}$	$\dot{ENC}$
	(1)	(2)	(3)	(4)	(5)	(6)
Early States SAH_{it}	-4.454^{**}	-6.088^{***}	-6.895^{***}			
	(2.074)	(1.455)	(1.223)			
All States SAH_{it}				-5.508^{***}	-5.196^{***}	-4.621^{***}
				(1.036)	(0.721)	(0.654)
State + Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort Pre-Trends	No	No	No	No	No	No
$\bar{Y}$	-26.59	-40.43	-55.22	-26.59	-40.43	-55.22
N	3,366	3,366	3,300	3,366	3,366	3,300
Adjusted R^2	0.926	0.970	0.968	0.929	0.972	0.968

* $p < 0.10$, ** $p < 0.05$, ** $p < 0.01$. Standard errors are clustered at the state level. These models estimate the effect of statewide stay-at-home mandates on travel activity and social distancing. The dependent variables measure the percentage point changes in average distances traveled, visits to non-essential businesses, and unique human encounters for the same day of the week relative to the pre-COVID-19 baseline level (average of Feb 10 - Mar 8). A coefficient of one indicates a marginal effect of a 1 percentage point increase in travel relative to pre-COVID-19 levels, controlling for time and the average COVID-19 mobility change in the state during the sample period.

C.2 Event Study Models

Figure 10: Event Study, Un-residualized Changes in Average Distance Traveled, Full Sample, All Control Units

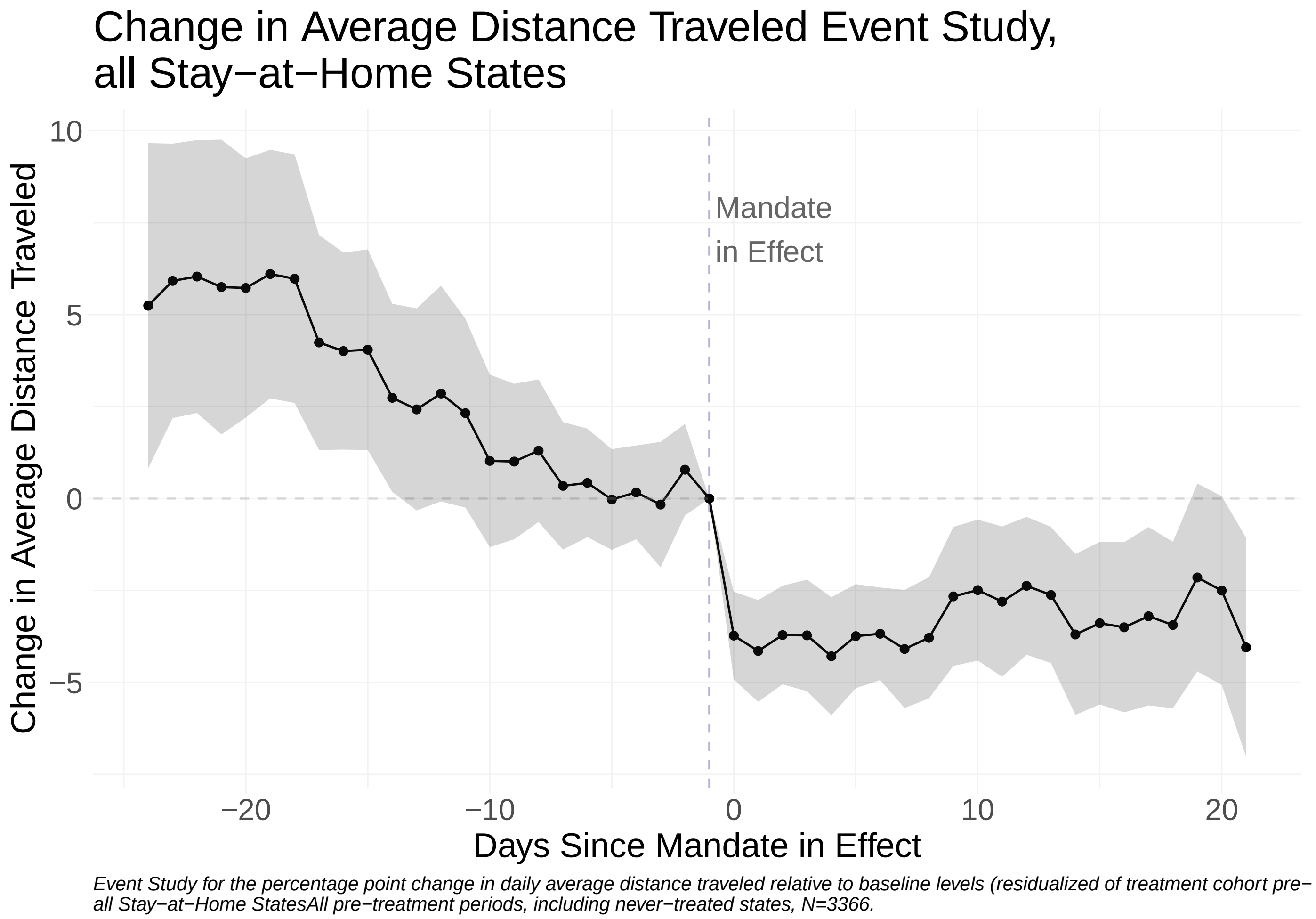


Figure 11: Event Study, Un-residualized Changes in Average Distance Traveled, Full Sample, SAH States Only

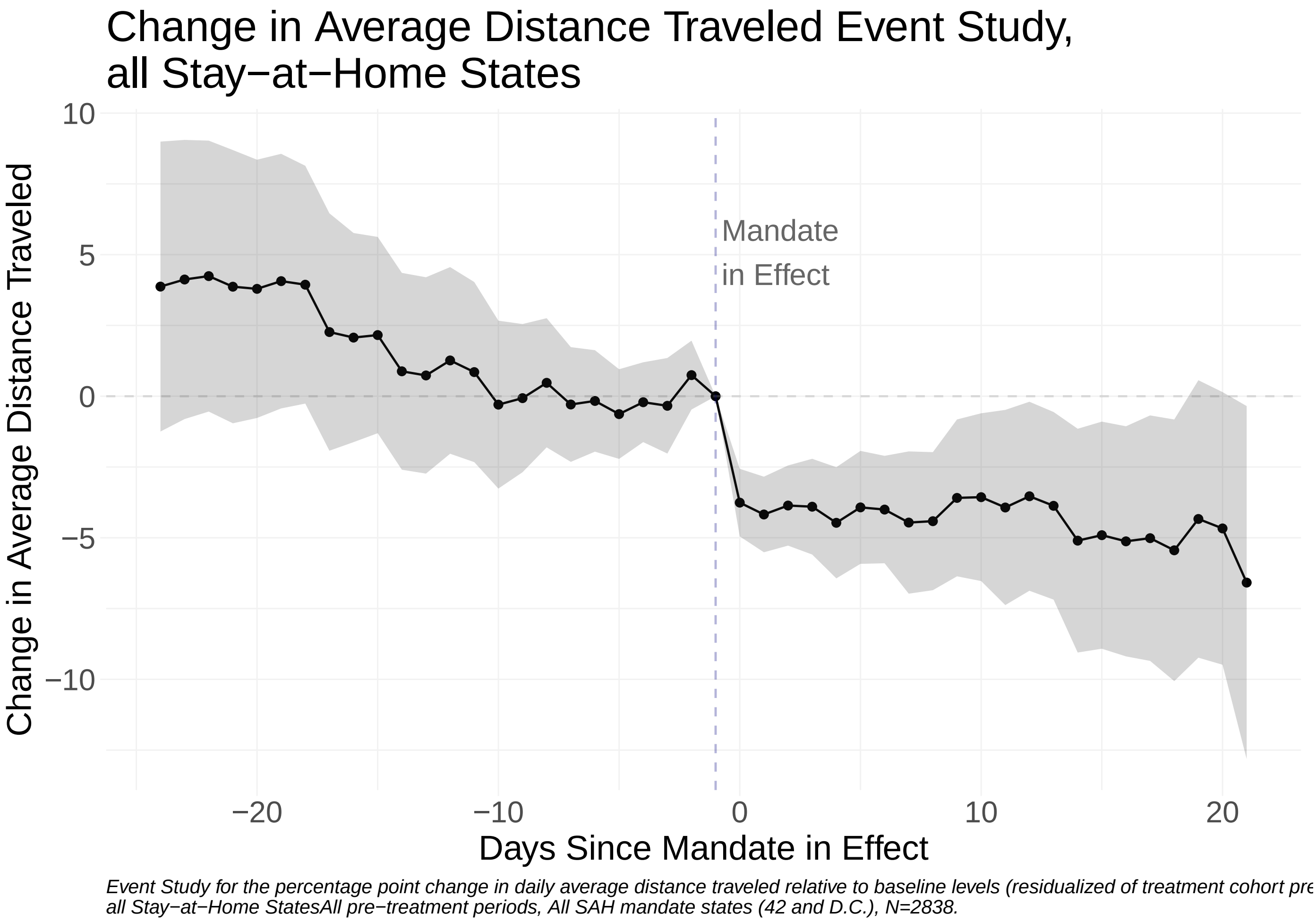


Figure 12: Event Study, Un-residualized Non-Essential Visits, Full Sample, All Control Units

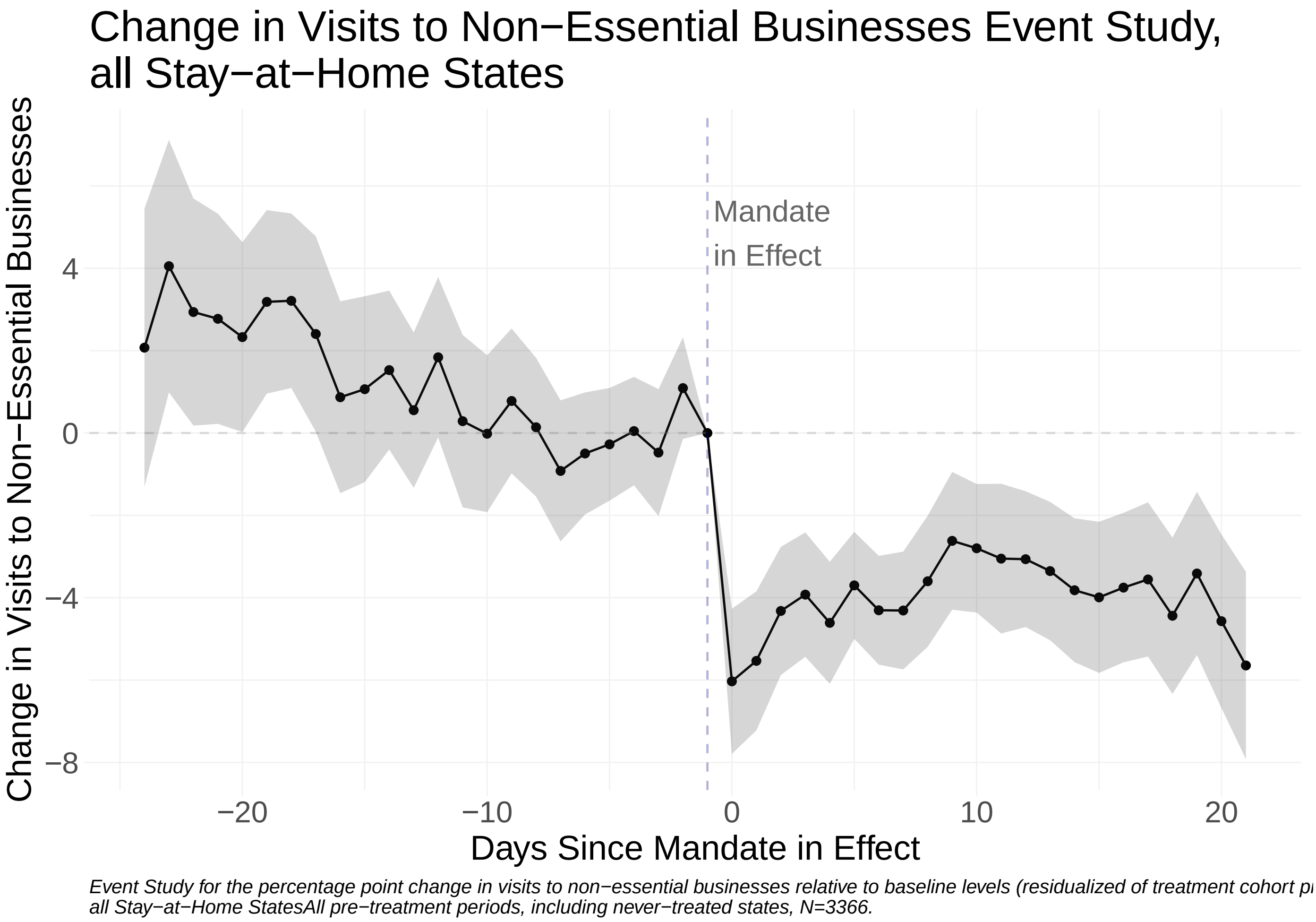


Figure 13: Event Study, Un-residualized Non-Essential Visits, Full Sample, SAH States Only

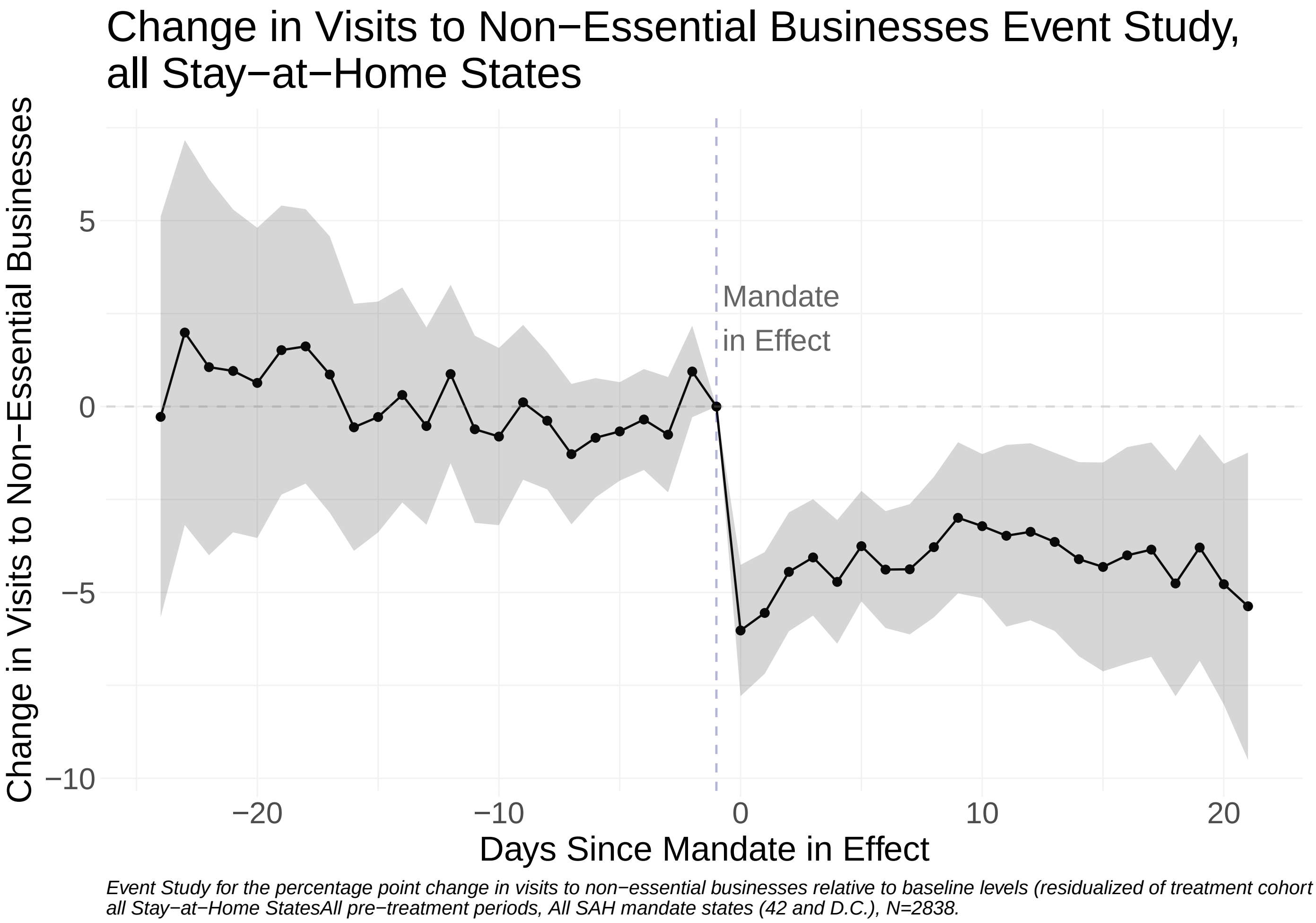
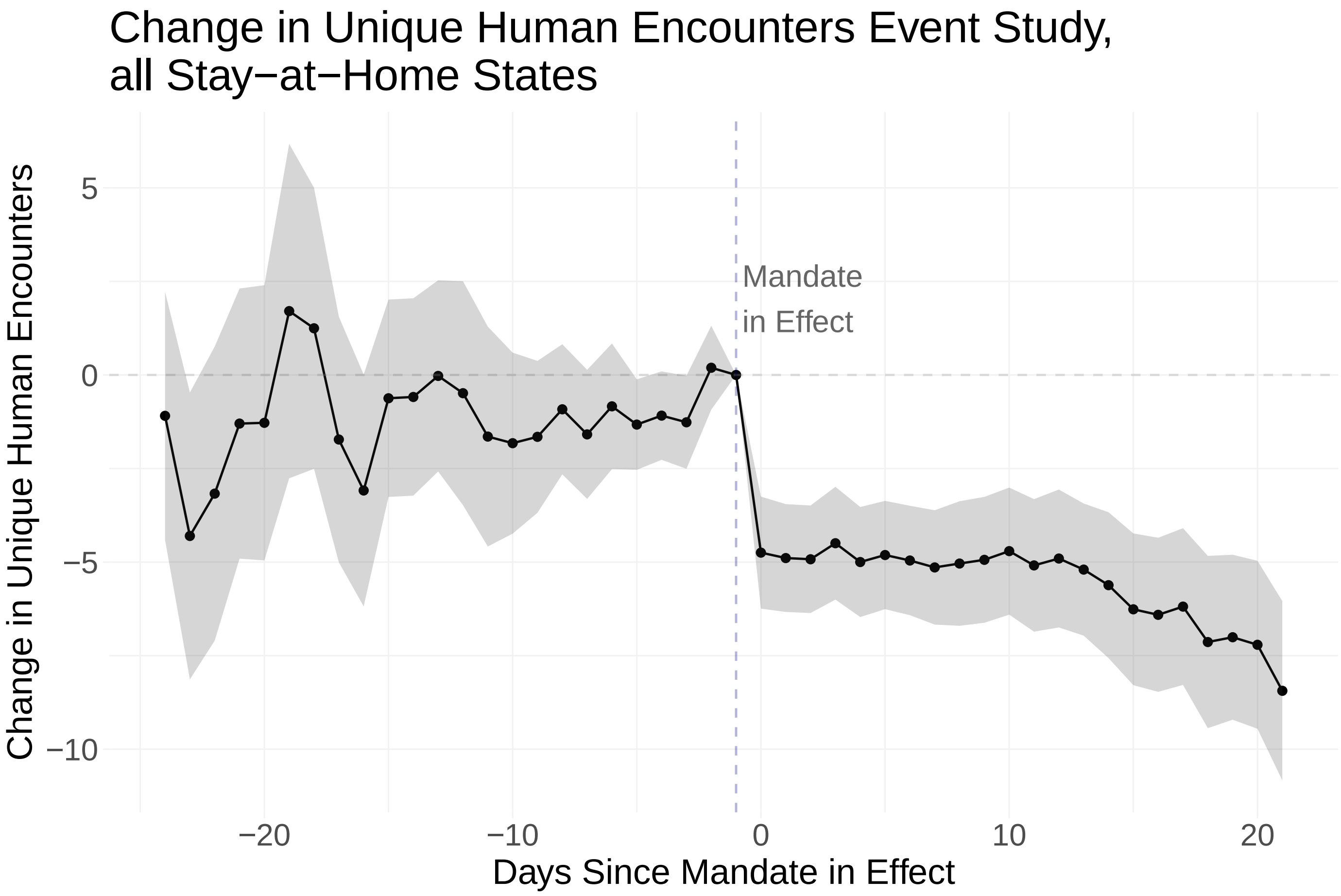
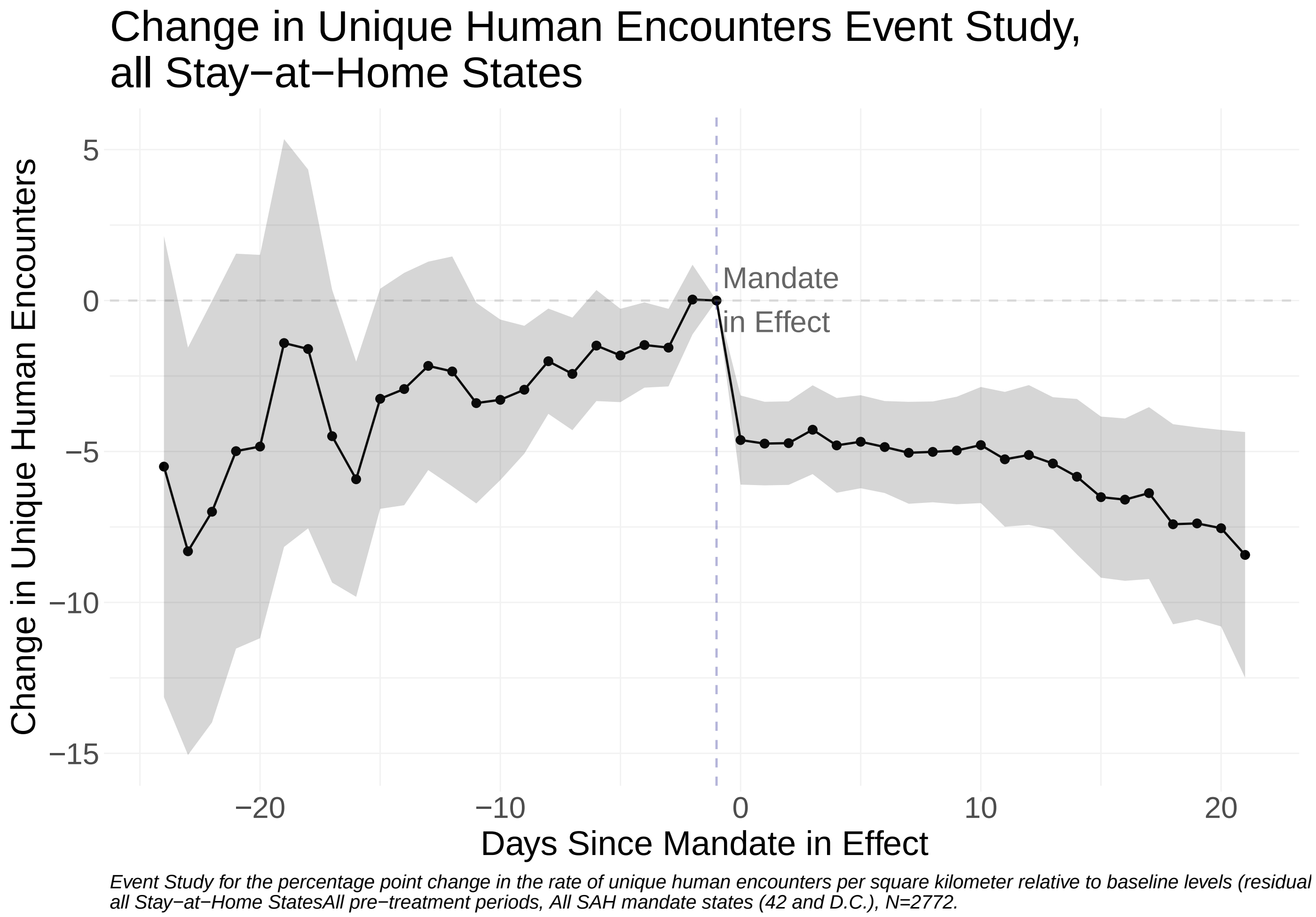


Figure 14: Event Study, Un-residualized Human Encounter Rate, Full Sample, All Control Units



Event Study for the percentage point change in the rate of unique human encounters per square kilometer relative to baseline levels (residual all Stay−at−Home StatesAll pre−treatment periods, including never−treated states, N=3300.

Figure 15: Event Study, Un-residualized Human Encounter Rate, Full Sample, SAH States Only



D Weighted Event Study

D.1 Partially Pooled Synthetic Control Method

Partially pooled SCM integrates the two most common ad-hoc approaches (applying synthetic control separately to each treated unit before taking an average across treated units, and estimating weights to fit the average pre-treatment outcome for all treated units) in a manner that simultaneously minimizes error arising from both the single-unit fits and the pooled fit [6]. While the approach does not guarantee perfect balance of both unit-specific and overall pre-treatment outcomes, it offers a way to minimize the sources of bias associated with each choice on its own.

Let $Y_{it}(1)$ be the potential outcome for unit i in period t after having received the treatment, and let $Y_{it}(0)$ be the potential outcome for a unit in the absence of treatment (i.e. a unit that has yet to receive treatment or never receives the treatment). In our setting, 43 units eventually adopt a stay-at-home mandate (42 states and Washington D.C.), and are denoted by $W_i = 1$. $W_i = 0$ for the eight states that never adopted a mandate. We can then express the observed outcome for the units that adopt a mandate at time T_i as $Y_{it} = Y_{it}(0)\mathbb{I}\{t < T_i\} + Y_{it}(1)\mathbb{I}\{t \geq T_i\}$ and as $Y_{it} = Y_{it}(0)$ for the never-mandate states.

In this framework, an estimate for the average treatment effect on the treated (ATT) is given by

$$ATT_k = \frac{A}{J}\sum_{j=1}^{J} Y_{j,T_j+k}(1) - \hat{Y}_{j,T_j+k}(0) = \frac{A}{J}\sum_{j=1}^{J} Y_{j,T_j+k}(1) - \sum_{i=1}^{N} \hat{\tau}_{ij} Y_{i,T_{j+k}}$$

where k indicates the "event time" elapsed relative to the treatment time T_j, given by $k = t - T_j$. $Y_{j,T_j+k}(1)$ is observed for all treated units after mandate adoption, and following [6] the unobserved potential outcome $\hat{Y}_{j,T_j+k}(0)$ is obtained through a modified SCM approach using the available donor pool at time $T_j + k$ (units that have yet to receive treatment or never receive treatment). For treated units $j_1, ..., j_J$, the N-vector SCM weights $\hat{\tau}_j$ are the solution to the partially pooled SCM optimization problem:

$$\min_{\tau_1,\ldots,\tau_J \in \triangle_j^{scm}} \frac{\nu}{2} q^{pool}(\Gamma) + \frac{1-\nu}{2} q^{sep}(\Gamma) + \lambda \sum_{j=1}^{J} \sum_{i=1}^{N} f(\tau_{ij}) \tag{4}$$

In contrast to [1], weights are based solely on lagged outcomes with the potential addition of the penalization term $\lambda \sum_{j=1}^{J} \sum_{i=1}^{N} f(\tau_{ij})$ to promote uniformity.[1] q^{pool} is the mean square error for the average of the pre-treatment periods across all J treated units when running SCM separately for each unit, and q^{sep} is the equivalent object when SCM is applied to the "pooled" average of all treated units. $\nu \in [0, 1]$ is the hyperparameter determining the weight given to each SCM approach; a value of $\nu = 0$ corresponds to separate SCM weights while $\nu = 1$ yields weights derived from the pooled SCM approach. In this way, the partially pooled SCM weights trade off imbalance resulting from state-specific matches with the pooled imbalance; see [6] for additional discussion of the balance possibility frontier.

The partially pooled SCM approach can obtain a causal estimate of the average treatment effect on the treated (ATT) under two key assumptions [5]. First, we assume that a treated unit's potential outcomes prior to receiving treatment are equal to the control unit's potential outcomes: $Y_{it}(s) = Y_{it}(0)$ for $t < s$. This assumption serves as a generalization of SUTVA, ruling out interference across states in our setting [14]. Second, we must assume that, for a given unit with $W_i = 1$, the potential outcomes following treatment are identical to the observed treated potential outcome: $Y_{it}(s) = Y_{it}(1)$ for any $0 < s \leq t$. This assumption imposes stability of the treatment effect over time within a given unit while still allowing $\{Y_{it}(0), Y_{it}(1)\}$ to vary across units.

Weighted Event Studies

To correct for imperfect pre-treatment balance in partially pooled SCM, we augment the partially pooled SCM estimator with a fixed effects outcome model and estimate weighted event studies. Synthetic controls are constructed based on the balance of residualized pre-treatment outcomes; in this way, the approach builds upon recent research on doubly-robust estimators with an extension to the staggered adoption setting [2, 3, 4, 6, 7].

The weighted event study obtains the counterfactual for treated unit j, k periods after adopting a mandate, as

$$\hat{Y}^{aug}_{j,T_j+k} = \hat{m}_{ijk} + \sum_{i=1}^{n} \hat{\tau}^*_{ij}(Y_{i,T_j+k} - \hat{m}_{ijk}) \tag{5}$$

Where $\hat{\tau}^*_{ij}$ are partially pooled SCM weights obtained using residualized outcomes and $\hat{m}_{ijk}$ is obtained as the uniformly-weighted average of pre-period outcomes, equivalent to augmentation with unit fixed effects. This approach yields a unit-specific ATT estimate k periods post-adoption as

$$\widehat{ATT}^{aug}_{jk} = \left(Y_{j,T_j+k} - \sum_{\ell=1}^{T_j-1} \frac{1}{T_j - 1} Y_{i,T_j-\ell}\right) - \sum_{i=1}^{N} \hat{\tau}^*_{ij}\left(Y_{i,T_j+k} - \sum_{\ell=1}^{T_j-1} \frac{1}{T_i - 1} Y_{i,T_j-\ell}\right) \tag{6}$$

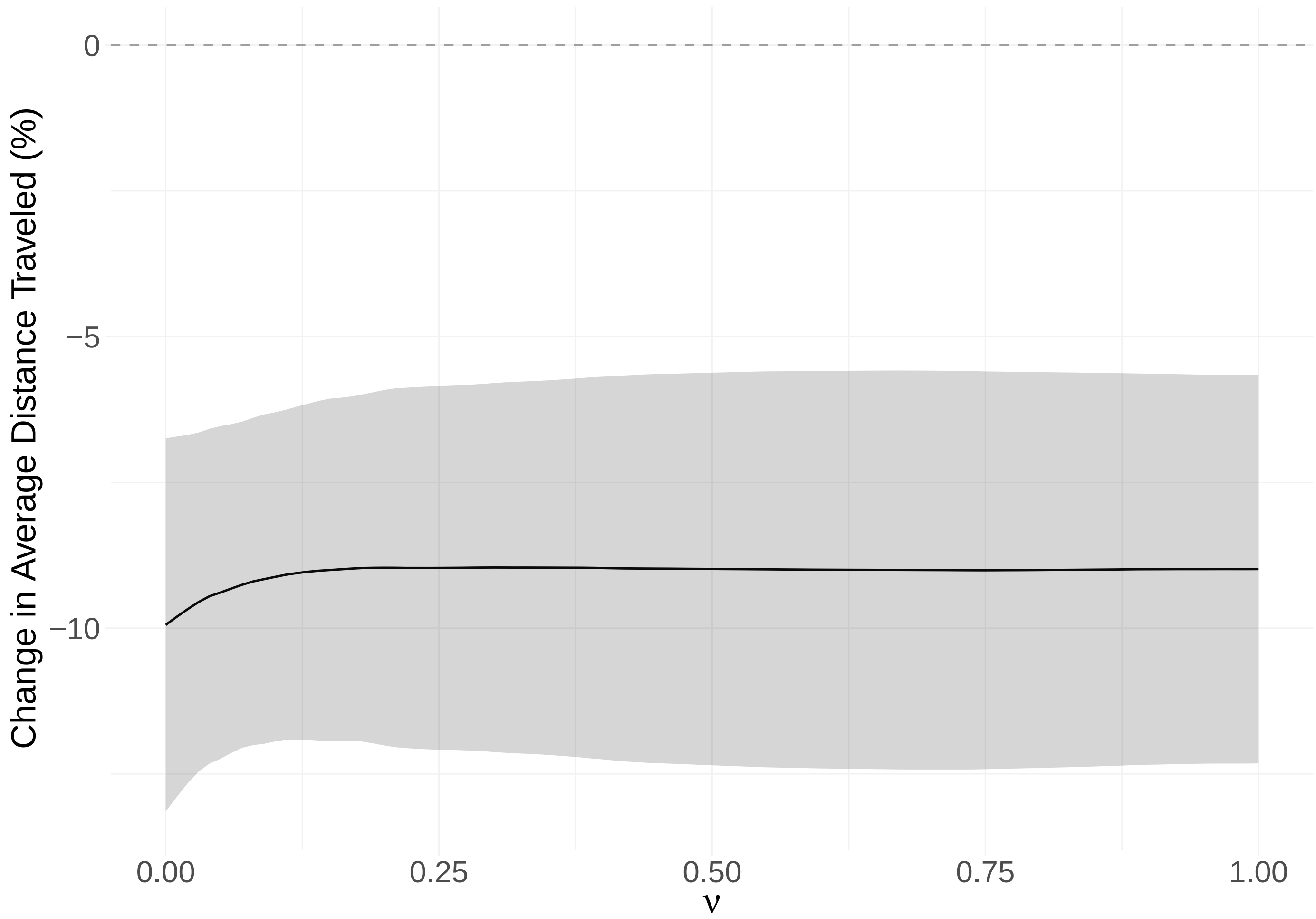
This approach builds upon the robustness properties of the intercept-shifted or de-meaned SCM estimators in a way that allows for staggered adoption [**?**, **?**]. $\widehat{ATT}^{aug}_{jk}$ can be thought of as a doubly-weighted difference in differences estimator, wherein the change in the treatment unit is obtained as the difference between the treatment unit's outcome in period k and its pre-period average, and the change in the control group is the average for equivalent changes for all donor units, weighted by partially pooled synthetic control weights. Averaging $\widehat{ATT}^{aug}_{jk}$ across all treated units at a given point in event time yields a period-specific treatment effect $\widehat{ATT}^{aug}_{k}$ that can be thought of as equivalent to the typical dynamic ATT obtained from an event study design. Averaging across all post-treatment periods yields the overall treatment effect estimate, $\widehat{ATT}^{aug}$. Standard errors are obtained using a jackknife approach [4].

[1] We set $\lambda = 0$ for our estimation because we have a sufficiently large donor pool to obtain pre-treatment balance.

D.2 Weighted Event Study Estimates across ν

Figures 16, 17, and 18 plot the overall ATT estimates for each travel outcome across possible values of ν, illustrating how a shift from separate to pooled SCM weights affect our conclusions. Estimates across all three mobility measures remain highly stable for any choice of ν. When fitting separate synthetic controls to each state ($\nu = 0$), we obtain an overall ATT estimate for average distance traveled of -9.94. As the weighting shifts to pool SCM weights, the ATT estimate rises slightly before reaching its maximum at -8.96 with $\nu = 0.30$ and falling to -8.99 for a purely pooled SCM control. Estimated mandate effects for encounter rates yield a similar shape, beginning with a minimum of -4.16 for separate SCM and peaking at -3.51 at $\nu = 1$ for the fully pooled SCM. Trips to non-essential visits begins at a value of -0.81 for separate SCM and reaches a minimum of -1.08 for the perfectly pooled case.

Figure 16: Overall Weighted Event Study ATT Estimates by ν, Average Distance Traveled



E Health Analyses: Robustness

The following table and figures report results from alternate specifications of the difference-in-differences and event study models for mortality and morbidity impacts of stay-at-home mandates.

E.1 Difference-in-Differences Models

Table 13: Stay-at-Home Mandates and COVID-19 Death Rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SAH_{it}	0.975*	0.959*	0.906*	0.837*	0.159***	0.157***	−0.140	−0.169*
	(0.488)	(0.481)	(0.480)	(0.469)	(0.058)	(0.058)	(0.095)	(0.096)
$\dot{ADT}\times$ Pre-Period				0.013				0.006
				(0.009)				(0.007)
$\dot{VIS}\times$ Pre-Period				0.007				0.026*
				(0.015)				(0.014)
$\dot{ENC}\times$ Pre-Period				0.005				0.005
				(0.006)				(0.007)
$\bar{Y}$	0.21	0.21	0.3	0.3	0.21	0.21	0.3	0.3
Pre-Period $\bar{Y}$	0.0017	0.0007	0.0014	0.0016	0.0017	0.0007	0.0014	0.0016
Treatment Group	Early	Early	Early	Early	All	All	All	All
State + Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort Pre-Trends	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Mobility Pre-Trends	No	No	No	Yes	No	No	No	Yes
Pre-Periods Used	All	All	2 Weeks	2 Weeks	All	All	2 Weeks	2 Weeks
N	3,366	3,366	2,288	2,245	3,366	3,366	2,288	2,245
Adjusted R^2	0.512	0.506	0.550	0.559	0.458	0.454	0.523	0.538

* $p < 0.10$, ** $p < 0.05$, ** $p < 0.01$. Standard errors are clustered at the state level. These models estimate the effect of statewide stay-at-home mandates on COVID-19 death rates per 100,000 population. Columns (1)-(4) report estimates for early stay-at-home mandates (CA, IL, NJ, and NY) while Columns (5)-(8) report estimates for all states that ever adopt statewide mandates (42 and D.C.). *Cohort Pre-Trends* indicate outcomes de-trended by treatment cohort-specific linear trends (Goodman-Bacon 2018). *Mobility Pre-Trends* control for $\dot{ADT}$, $\dot{NEV}$, and $\dot{ENC}$ in the pre-treatment period (prior to March 19). *2 Weeks* indicates sample trimmed to 2 weeks before each states' mandate, and March 19 for never-mandate states.

Table 14: Stay-at-Home Mandates and COVID-19 Hospitalization Rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SAH_{it}	0.033	-5.282^{**}	-0.035	-0.037	-5.597^{**}	-0.129	-6.038^{**}
	(0.188)	(2.590)	(0.193)	(0.206)	(2.654)	(0.225)	(2.777)
$\dot{ADT}\times$ Pre-Period		0.033^{*}			0.034^{*}		0.035^{*}
		(0.018)			(0.018)		(0.019)
$\dot{VIS}\times$ Pre-Period		0.013			0.011		0.007
		(0.018)			(0.018)		(0.020)
$\dot{ENC}\times$ Pre-Period		0.045^{*}			0.050^{*}		0.056^{*}
		(0.025)			(0.026)		(0.028)
$\bar{Y}$	0.21	0.21	0.03	0.30	0.21	0.21	0.30
Pre-Period $\bar{Y}$	0.07	0.07	0.07	0.19	0.19	0.07	0.07
Treatment Group	All	All	All	All	All	All	All
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort Pre-Trends	No	No	No	No	No	No	No
Mobility Controls	No	Pre	3wk	No	Pre	No	Pre
Sample	All	All	All	2wk Pre	2wk Pre	SAH	SAH
N	1,122	1,122	1,111	1,084	1,084	916	916
Adjusted R^2	0.592	0.594	0.596	0.596	0.598	0.586	0.589

* $p < 0.10$, ** $p < 0.05$, ** $p < 0.01$. Standard errors are clustered at the state level. These models estimate the effect of all statewide stay-at-home mandates on COVID-19 hospitalization rates per 100,000 population. *Pre* mobility controls account for $\dot{ADT}$, $\dot{NEV}$, and $\dot{ENC}$ prior to each state's mandate, while *3wk* controls for average mobility changes for each of the prior 3 weeks. *2wk Pre* indicates sample trimmed to 2 weeks before each states' mandate and March 19 for never-mandate states, while *SAH* limits the sample to the states that ever adopt statewide mandates (42 and D.C.).

Figure 17: Overall Weighted Event Study ATT Estimates by ν, Non-Essential Visits

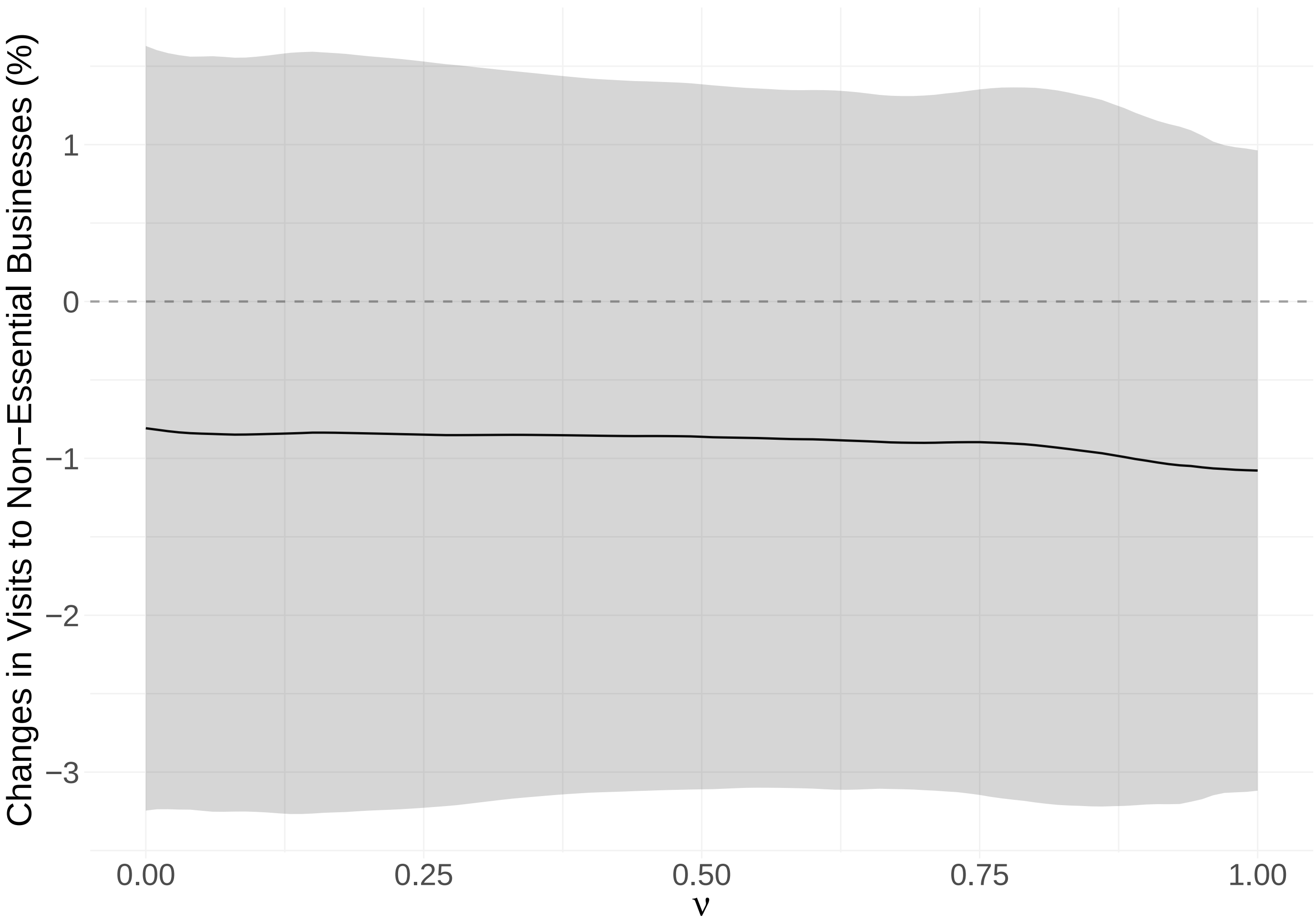
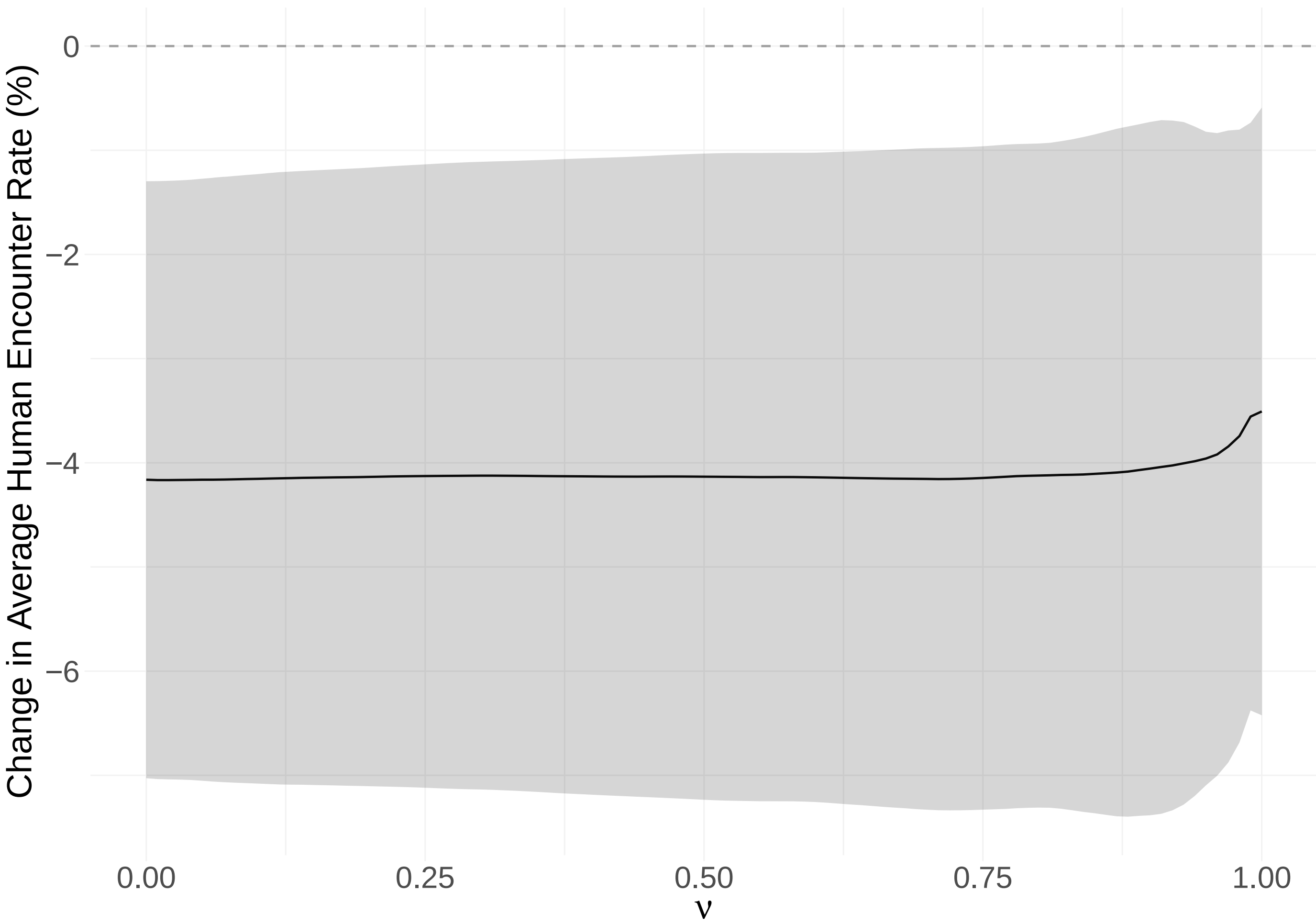


Figure 18: Overall Weighted Event Study ATT Estimates by ν, Human Encounter Rate



E.2 Event Study Models

Figure 19: Event Study, COVID-19 Residualized Death Rates, Pre-Period Mobility Controls, Full Sample

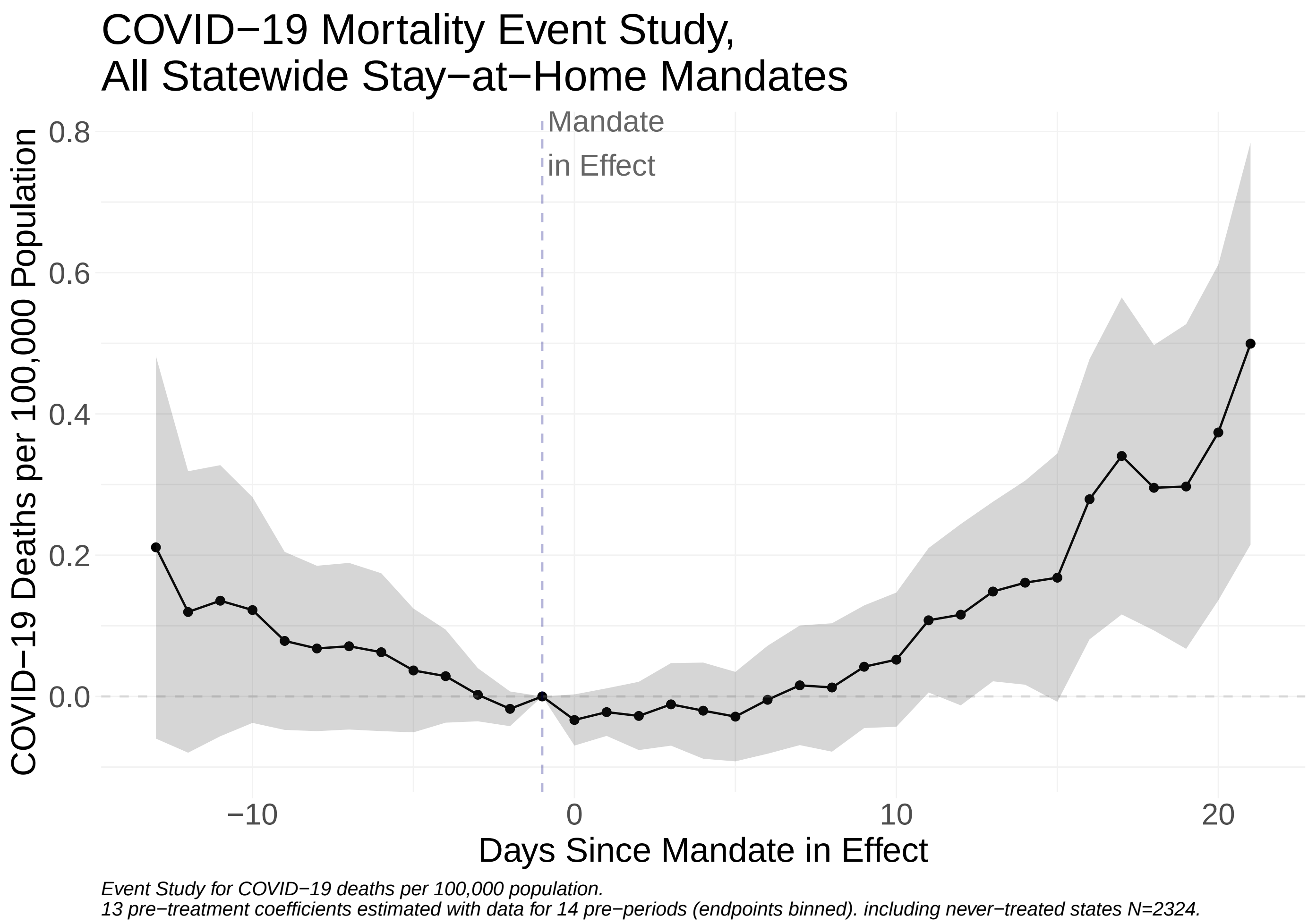


Figure 20: Event Study, COVID-19 Hospitalization Rates,2 Week Pre-Mandate Sample, SAH States Only

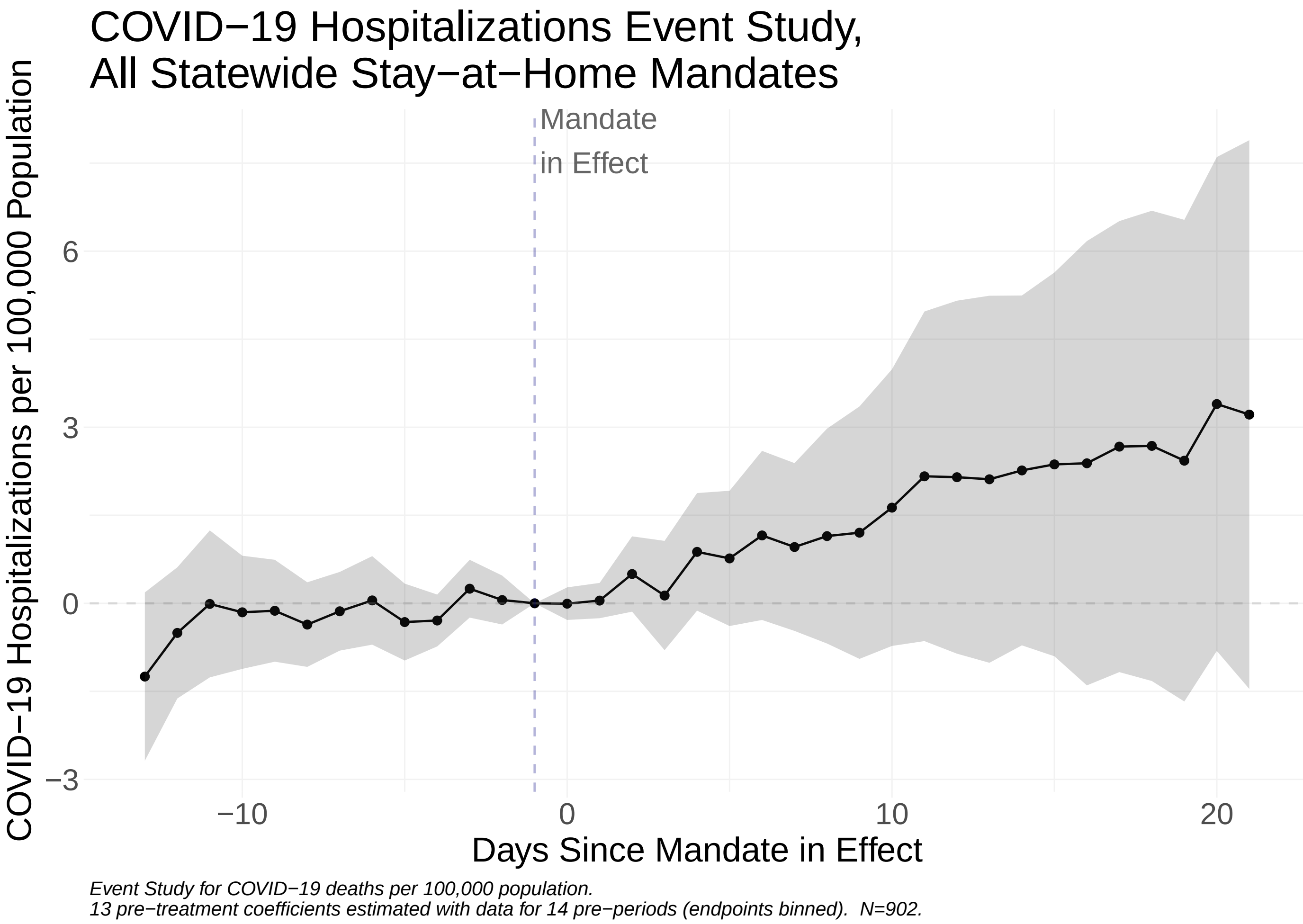


Figure 21: Event Study, COVID-19 Residualized Death Rates, Pre-Period Mobility Controls, No Control Units, 1 Week Pre-Periods

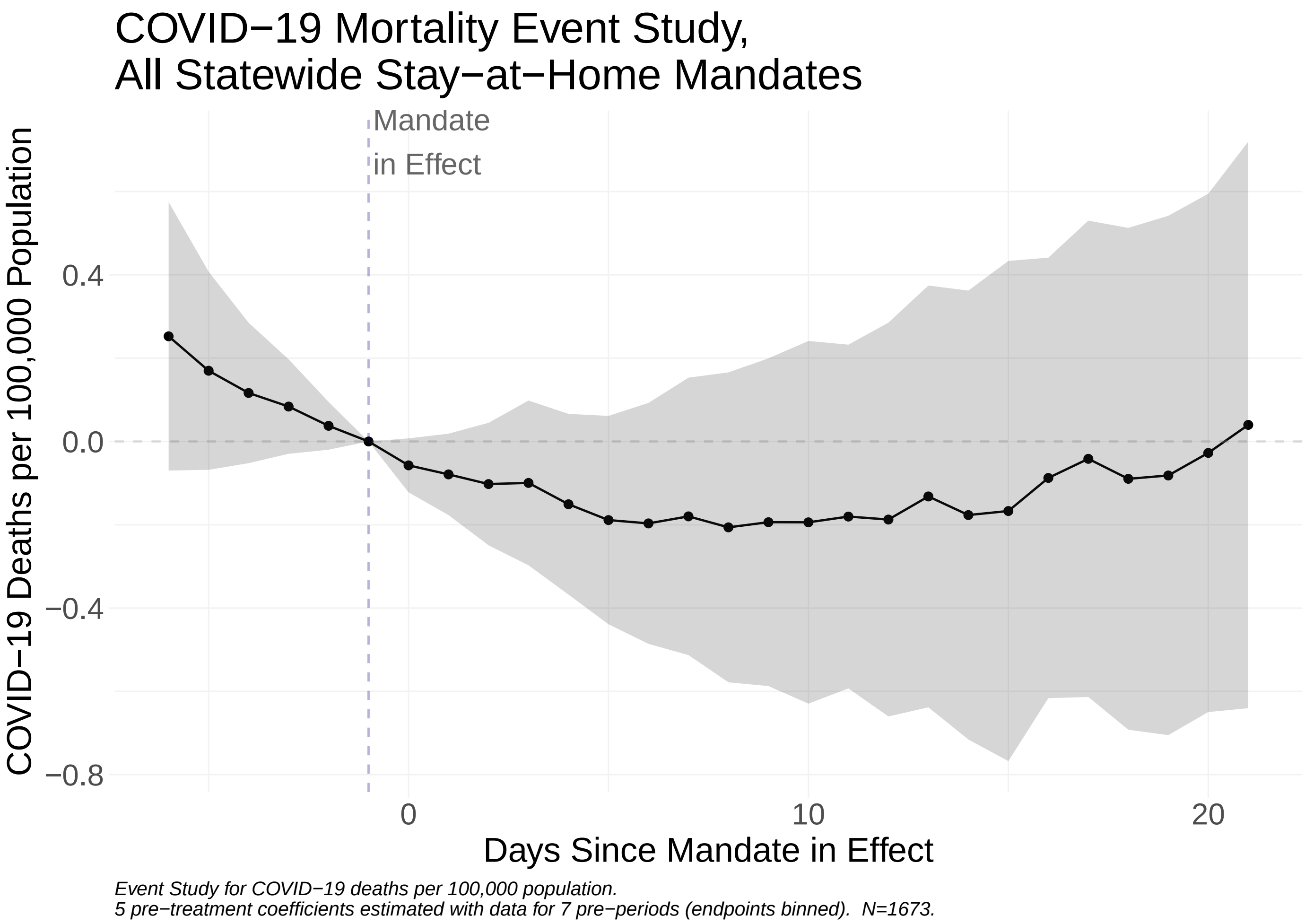
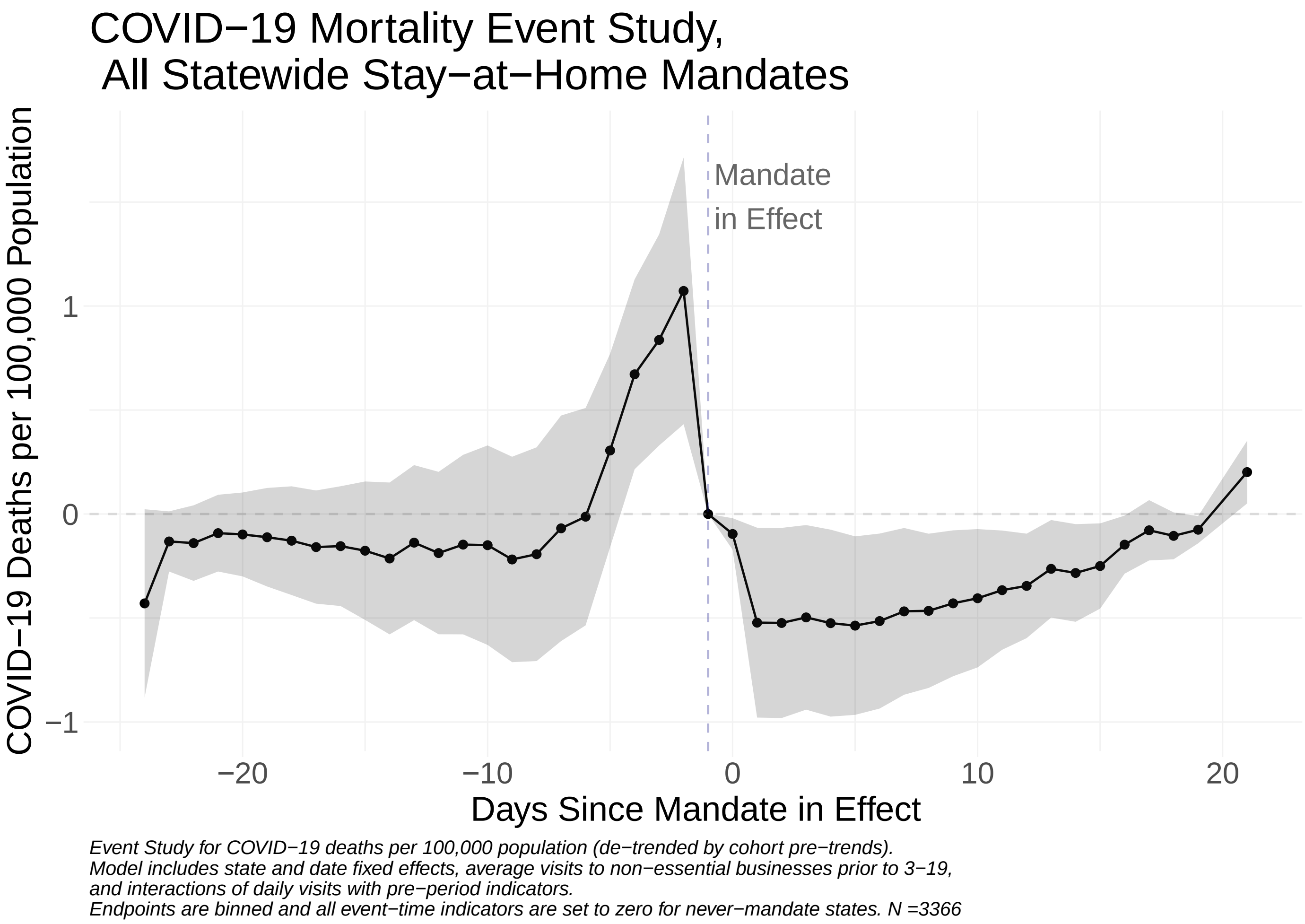


Figure 22: Event Study, COVID-19 Residualized Death Rates, Pre-Period Control Interactions, No Never-Mandate Units, Pre-Period In



F Complementary Analysis Using Google's COVID-19 Community Mobility Reports

To understand how our findings persist across alternate measures of travel activity and social distancing, we next replicate results using data obtained from Google's COVID-19 Community Mobility Reports [10].

F.1 Correlations of Google Measures and Unacast Measures

First, we provide a comprehensive comparison of the Unacast data to the Google Mobility Report data [10]. We provide evidence that the data we employ is nearly perfectly correlated with this other source, such that our findings are not likely due to spurious measurement in the specific source of data used.

We compare the Unacast measures to comparable data from google, as a full correlation analysis between each of the three Unacast measures and the available google mobility trend measures. The correlation tables are provided here and referenced in the main paper when we discuss how Unacast data-set compares to other available data, attesting to the quality of the measures used in the paper.

The change in distance traveled measure we use displays very high correlations with travel data produced by other sources. To investigate the validity of our measures, we compare all the three Unacast measures with the mobility report measures form the Google's COVID-19 Community Mobility Report for the relative change for retail and recreation travel.[2] Table 15 reports the minimum, average, and maximum correlations between state specific Unacast and google mobility measures. In column 1 we focus on the correlations between changes in average distance traveled (CADT) and the Google measure related to recreation and retail. Column 2 focuses on correlations between Unacast measure for non essential visits (NEV) and the google recreation and retail measure. We see that the lowest state correlation between CADT and google is for the state of Wyoming, with a correlation of 0.75, and the lowest state correlation between NV and google is for the state of Mississippi, with a correlation of 0.961.

Table 15: Average, Min, and Max Correlations by State, Unacast and Google Activity Measures

	Google and $\dot{ADT}$	Google and $\dot{NEV}$
Min	0.750	0.962
Average	0.949	0.981
Max	0.988	0.993

Source: Google and Unacast. This table presents minimum, average, and maximum correlations by states between the Google "Retail and Recreation" measure and the utilized measures of changes in average distance traveled ($\dot{ADT}$) and non-essential visits ($\dot{NEV}$) obtained from Unacast. The minimum correlation for $\dot{ADT}$ is WY, and the minimum correlation for $\dot{NEV}$ is for MS.

The full set of correlations by state is given in Table 16. Overall the levels of correlation are very high, and do not vary systematically between states that adopt mandates and those that never adopt such policies. For instance, for California we observe a correlation of 0.97, while for New York we observe a correlation of 0.98. The activity measures remain highly correlated when considering all the states. These strong relationships across data providers suggest that our results are indicative of general mobility patterns and not spurious, arising from anomalies of our chosen data source.

[2] Google. 2020. "COVID-19 Community Mobility Reports." Accessed March 27, 2020.

Table 16: Correlations Between Google Retail and Rec Measure and Unacast Measures by State

State	corr(Google,CADT)	corr(Google,NEV)
AK	0.956	0.963
AL	0.952	0.966
AR	0.931	0.963
AZ	0.976	0.984
CA	0.976	0.983
CO	0.979	0.988
CT	0.970	0.983
DC	0.980	0.988
DE	0.962	0.983
FL	0.988	0.987
GA	0.965	0.979
HI	0.943	0.985
IA	0.907	0.976
ID	0.907	0.978
IL	0.960	0.987
IN	0.926	0.985
KS	0.955	0.976
KY	0.937	0.982
LA	0.964	0.971
MA	0.979	0.985
MD	0.972	0.986
ME	0.936	0.978
MI	0.968	0.987
MN	0.963	0.982
MO	0.956	0.977
MS	0.956	0.962
MT	0.886	0.986
NC	0.956	0.977
ND	0.911	0.987
NE	0.943	0.980
NH	0.938	0.976
NJ	0.977	0.979
NM	0.938	0.982
NV	0.984	0.993
NY	0.980	0.989
OH	0.945	0.986
OK	0.962	0.974
OR	0.950	0.987
PA	0.957	0.988
RI	0.969	0.979
SC	0.956	0.980
SD	0.906	0.981
VA	0.973	0.985
VT	0.961	0.978
WA	0.967	0.983
WI	0.934	0.980
WV	0.941	0.983
WY	0.750	0.980

Source: Google and Unacast. Min correlation CADT and google is WY, and the minimum correktion between NEV and google measure MS.

G Complementary Analysis of Stay-at-Home Mandate Effects on Mobility using Google Mobility Data

We estimate the model of changes in mobility measures as a function of mandate treatment controlling for state-specific trends. Tables 17 and 18 present the results for all mandates and for the first four mandates separately. We see in Table 17 the estimated average treatment effects for the early first 4 mandates, where each column

Table 17: Effect of Early States' Stay-at-Home Mandates, Google Analysis

	(1) Gro/Phar	(2) Park	(3) Ret/Rec	(4) Transit	(5) Work	(6) Home
SAH_{it}	-0.148***	-0.111	-0.049***	0.014	-0.023*	0.014**
	(0.026)	(0.083)	(0.018)	(0.015)	(0.013)	(0.006)
N	2856	2856	2855	2856	2855	2856
R^2	0.910	0.481	0.976	0.973	0.962	0.974
F	170.801	14.651	868.500	753.952	2107.570	942.221

Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. These models estimate the effect of the first four statewide stay-at-home mandates on Google's measures of travel activity from their COVID-19 Community Mobility Reports. The dependent variables measure the change in percentage points for the same day of the week relative to baseline levels for Grocery and Pharmacy (1), Parks (2), Retail and Recreation (3), Transit Stations (4), Workplace (5), Residential (6). All columns include state-specific cubic trends, state fixed effects, and day fixed effects.

corresponds to each of the six categories of google mobility measures. The category of grocery/pharmacy travel experiences a significant drop of 14.8 percentage points due to early implemented first 4 state mandates, the change for the park's category is not significant, retail and recreation category mobility drops significantly by 4.9 percentage points, and work mobility measure also drops significantly by 2.3 percentage points. There is no significant change in the transit category mobility measure and finally the measure for staying at home increases significantly by 1.4 percentage points due to the first 4 early mandates.

Table 18: Effect of All States' Stay-at-Home Mandates, Google Analysis

	(1) Gro/Phar	(2) Park	(3) Ret/Rec	(4) Transit	(5) Work	(6) Home
SAH_{it}	-0.088***	-0.182***	-0.062***	-0.026***	-0.029***	0.017***
	(0.007)	(0.033)	(0.005)	(0.005)	(0.003)	(0.002)
N	2856	2856	2855	2856	2855	2856
R^2	0.917	0.487	0.977	0.973	0.962	0.974
F	184.717	14.552	933.192	769.751	2269.409	996.257

Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. These models estimate the effect of all statewide stay-at-home mandates on Google's measures of travel activity from their COVID-19 Community Mobility Reports. The dependent variables measure the change in percentage points for the same day of the week relative to baseline levels for Grocery and Pharmacy (1), Parks (2), Retail and Recreation (3), Transit Stations (4), Workplace (5), Residential (6). All columns include state-specific cubic trends, state fixed effects, and day fixed effects.

Turning now to using all state mandates, we see in Table 18 the estimated average treatment effects for all mandates, where each column corresponds to each of the six categories of google mobility measures. The category of grocery/pharmacy travel experiences a significant drop of 8.8 percentage points due to implemented state mandates, the change for the parks category is significant and results in a drop of 18.2 percentage points, retail and recreation category mobility drops significantly by 6.2 percentage points, transit station mobility drops by 2.6 percentage points, and work mobility measure also drops significantly by 2.9 percentage points. Finally the measure for staying at home increases significantly by 1.7 percentage points due to the mandates.

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