The “10-Day Effect” of Statewide Shelter-in-Place Orders on Mobility

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Abstract

As a response to the COVID-19 public health crisis, most United States governors enacted statewide shelter-in-place policies in an attempt to reduce social contact and thereby slow the spread of the disease. Using measures of mobility at the county-level based on cell phone GPS data provided by UNACAST, we explore the extent to which these orders influenced the mobility behavior of Americans. To parse out the specific effect of statewide orders, we use an event study design, which leverages leads and lags of shelter-in-place policies to study variation in the outcome variable prior to and following the date of enactment. We find that the national trend of reduced movement began well before governors enacted these policies, so social distancing cannot be fully attributed to stay-at-home orders. However, our findings do suggest that there was a small yet significant change in mobility immediately before and for up to 10 days after these policies went into place. By comparison, this shift is not present when we examine state-level school closures or county-level shelter-in-place orders.

I. Introduction

The rapid onset and unprecedented scope of the COVID-19 pandemic has necessitated multidimensional public policy responses to rapidly and effectively inform behavior change. The virus was previously unknown before the outbreak began in Wuhan, China, in December 2019. Within the span of five months, COVID-19 has resulted in the deaths of over 108,000 Americans and has reached at least 1.89 million individuals across the United States. The disease spreads from person to person through small droplets from the nose or mouth that are expelled when an infected person coughs, sneezes, or speaks. Because symptomatic and asymptomatic individuals can be contagious, contact tracing to assess disease spread has been especially challenging. According to the Centers for Disease Control and Prevention (CDC), limiting face-to-face contact through social distancing is the single best way to prevent the spread of COVID-19.[1]

On March 13, 2020, the White House declared a state of national emergency in the United States. Shortly thereafter, several states and counties began enacting shelter-in-place (SIP) orders to reduce human interaction, and in turn, the likelihood of disease transmission in the absence of an effective vaccination. At the date of writing this paper, residents in a majority of states are still being instructed to stay at home as much as possible. The timing, severity, and enforcement of state orders, however, have significantly varied, with some governors holding off on imposing shelter-in-place orders altogether and instead favoring restrictions like public transportation closures. Given the wide range of policy responses taken to

[1] https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/social-distancing.html

contain the spread of the disease at each level of governance - ranging from closures of schools, parks, workplaces, and restaurants, to travel restrictions and election postponements - we are particularly interested in parsing out whether state-level shelter-in-place orders have had an impact on mobility, independent of national trends.

Understanding the extent to which state policies have had an impact, if any, on individual movement, will inform how political leadership should navigate the lifting of restrictions while prioritizing individual safety. Given the likelihood of additional waves of COVID-19, this insight can also inform state-level public health responses to disease resurgences or to outbreaks of new infectious diseases over the coming months and years.

Other researchers[2] have pointed out that a declining trend in mobility shows up in the data well before statewide SIP orders went into effect. These researchers have implied that the SIP orders had no effect on behavior. Although we observed this same trend (as described below), it is not necessarily the case that the SIP orders were completely ignored. We want to understand whether mobility behavior changed in any way in the days directly before and after state orders.

II. Research Question

The primary goal of our analysis is to explore the impact of state-level shelter-in-place orders on individual movement throughout the COVID-19 pandemic, using publicly available mobility data. Given broad trends in social distancing, public health campaigns, national media attention, as well as local policies, we hope to parse out whether state-level policy responses have had measurable and sustainable impacts on mobility, in order to inform future public health and policy decision-making. Our study uses an event study design, which leverages leads and lags of SIP policies to study variation in the outcome variable prior to and following the date of enactment.

III. Data

No single metric fully encapsulates social distancing compliance, mobility, or group interaction. Acknowledging this limitation, this study leverages anonymized, aggregated smartphone data from the Norwegian location data company UNACAST that measures individual movement at the county- level. Specifically, we use a daily measure of change in average distance traveled compared to a pre-Covid-19 baseline period as a proxy for social distancing.[3] The baseline is represented as the average distance traveled for the same county on the same weekday day over the four weeks prior to March 8, 2020. The data assigns an individual to a county based on where a device is present for the longest amount of time

[2] https://fivethirtyeight.com/features/americans-didnt-wait-for-their-governors-to-tell-them-to-stay-home-because-of-covid-19/

[3] Unacast. 2020. Unacast Social Distancing Dataset. https://www.unacast.com/data-for-good. (2020). Version from 25 May 2020.

each day, and the data follow 15-17 million devices. This study uses data collected from February through May 2020.

Our independent variable of interest is the date of each state SIP order. These data are compiled by Fullman et al. and are primarily sourced from individual state government websites. They are supplemented by the National Governors Association and the Kaiser Family Foundation online resources for coronavirus responses in the United States.[4] It is also important to track and control for county-level SIP policies that may impact local movement. Data on the date of each county-level SIP order was compiled by Wu et al.[5] at Johns Hopkins University, and are supplemented with data from the National Association of Counties. All of the above data sources are merged together in a time series format to facilitate a panel analysis.

IV. Methods

We employ an event study regression model to analyze the effect of statewide SIP policies in the days preceding and following their enactment. This model includes dummy variables to represent each of the days before and after the date of the order. We specifically focus on a span of two weeks, or 14 days, prior to each statewide policy, and four weeks, or 28 days, after each policy. This window allows us to examine variation in movement that occurs immediately before and after the policy change.

We employ the following model:

$$y_{c,d} = \alpha + \sum_{i=-1}^{i=-14} \beta(state\_sip\_policy\_date_{c,t+i}) + \sum_{i=1}^{i=28} \beta(state\_sip\_policy\_date_{c,t+i}) + \lambda_c + \theta_d + \omega X_{c,d} + \epsilon_{c,d}$$

where:

$y_{c,d}$ is the outcome variable, which in this case is the daily difference in movement (as a percentage change from a pre-COVID baseline) at the county level.

$state\_sip\_policy\_date_{c,t+i}$ indicates the days before or after the SIP policy enactment date for each county that is in a state with a SIP order. We included a coefficient for up to 14 days before the policy date and up to 28 days after the date.

λ_c and θ_d indicate county- and day-level fixed effects.

$X_{c,t}$ represents the controls that we include in the model to account for potential omitted variable bias. We included a binary variable for the existence of a county-level SIP order, and we include six dependent variable lags.

[4] https://github.com/COVID19StatePolicy/SocialDistancing
[5] https://github.com/JieYingWu/COVID-19_US_County-level_Summaries

$\epsilon_{c,t}$ is the error term.

The model is weighted by county population, to produce an estimate for the average person rather than the average county, and standard errors are clustered by county.

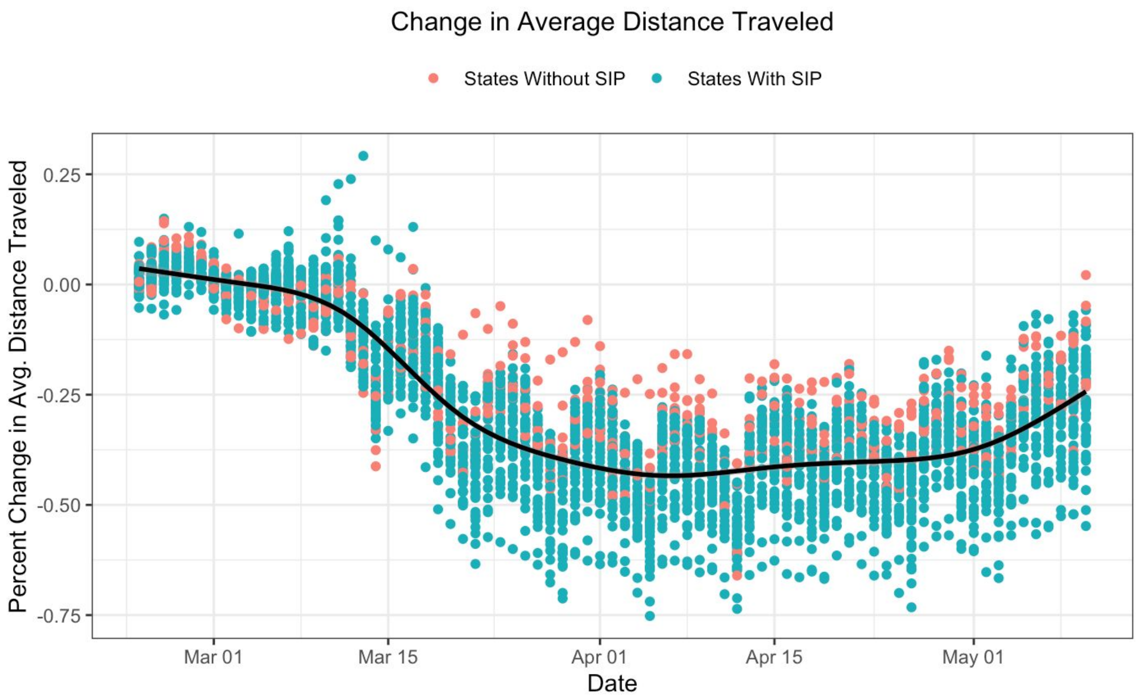
We also run several variations on this model to test our findings for robustness. More details on these variations are included in Appendix A.

To assert the impact of SIP policies, we must assume that the SIP order is the only important event that occurs on the day of a state's SIP order. In our analysis, we take advantage of the fact that states enacted SIP orders on different days, which makes this assumption more credible. However, it is still possible that some states enacted multiple policies on the same day that they enacted the SIP policy. For example, a state might have enacted a SIP order on the same day that it also closed parks and gathering spaces. If this is the case in many states, we could be wrongly attributing the observed effect to the SIP order.

V. Results

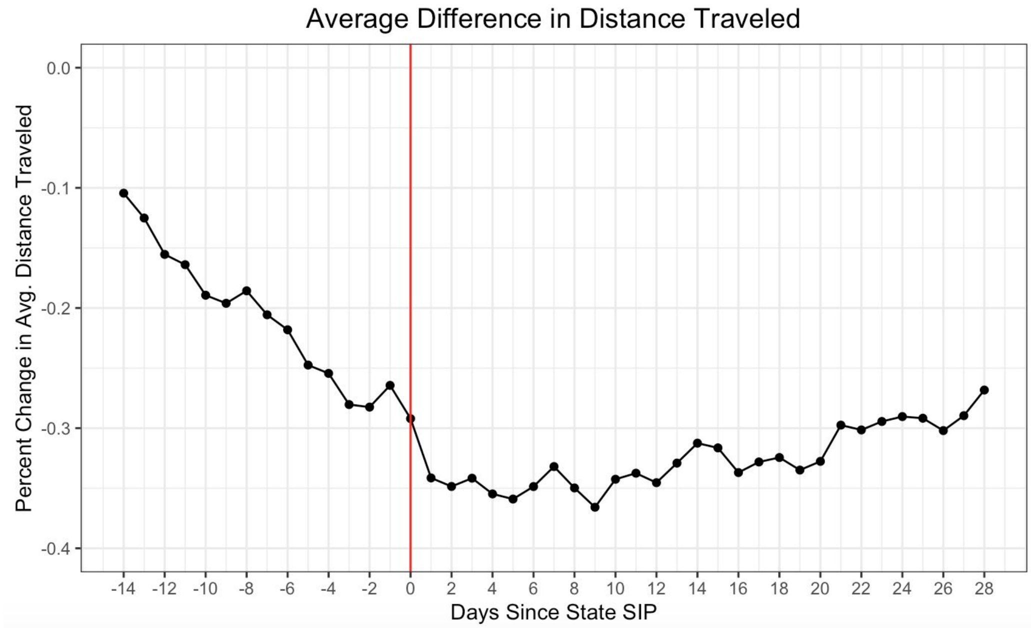
We begin by exploring the relationship between state-level SIP policies and changes in daily distance traveled from a pre-COVID-19 baseline. To better understand differential mobility between states that eventually have statewide SIP orders and those that do not, we first plot the percent change in average distance traveled against each date in the panel study. In Figure 1 below, each point represents an individual state on a given day between late-February and mid-May. It is evident that while all states demonstrate similar travel patterns prior to mid-March, states without SIP policies experience less of a relative reduction in movement than do states with SIP policies over the following two months. While it is certainly possible that states with and without SIP policies differ across other important features that contribute to mobility, this general clustering of the data does suggest the potential for a relationship between statewide SIP policies and social distancing.

Figure 1: Shifts in Mobility Among States with and without Statewide SIP Policies



Next, we focus on states that eventually have statewide SIP orders. For these locations, we calculate the average percent change in daily distance traveled by number of days relative to the respective statewide order (Day 0). In Figure 2 below, the x-axis represents days relative to a statewide SIP order, and the y-axis represents percent change in movement. We focus on two weeks (14 days) preceding and four weeks (28 days) following SIP orders.

Figure 2: Average Difference in Daily Distance Traveled Relative to SIP Order Date



Based on Figure 2, there is a reduction in movement that begins well in advance of the date of each state's SIP. This is not entirely surprising, as many events preceded state SIP policies. The first state SIP order (California) was enacted on March 19. By this date, the country's national public media sources had been reporting on the threat of COVID-19 and encouraging social distancing behaviors for several weeks. Also, the U.S. federal government had already declared COVID-19 to be a "public health emergency" on January 31 and a "national emergency" on March 13.[6] This downward trend does continue beyond the date of the order, but appears to plateau by approximately two days after the order goes into effect, on average.

Notably, on average, there appears to be a minor increase in movement the day immediately preceding a statewide SIP order. Then, between the day before and the day after SIP orders, there is a noticeable drop in average distance traveled from ~26% to ~34% below the baseline, representing an 8 percentage point reduction in movement.

To further explore this trend, we set up an event study in which we regress average change in daily distance traveled at the county level on a set of dummy variables representing number of days relative to the statewide SIP order. Again, we limit our analysis to a window of two weeks before and four weeks after SIP orders go into effect. We control for whether a given county also has a county-level SIP order in place on a given day using a binary indicator. Next, we include a set of six dependent variable lags, indicating mobility one through six days prior to the current day in the panel. We include these lags because we expect that the current level of mobility will be heavily determined by movement in the

6 https://www.whitehouse.gov/presidential-actions/proclamation-declaring-national-emergency-concerning-novel-coronavirus-disease-covid-19-outbreak/

preceding days, and therefore seek to account for potential omitted variable bias. To determine the effect of statewide SIP policies on the average person, we weight our model by county population and include both county and date fixed effects. Finally, we cluster standard errors by county.

Figure 3: Event Study Coefficients Before and After Statewide SIP Orders

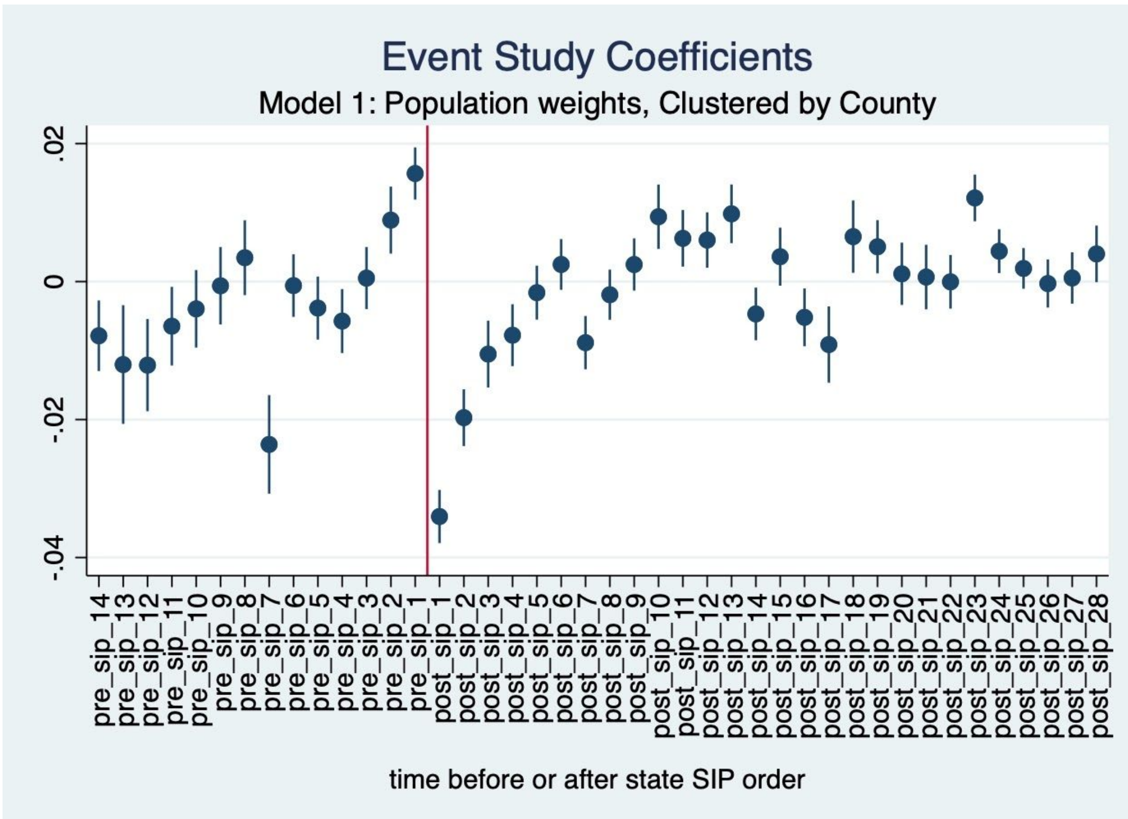
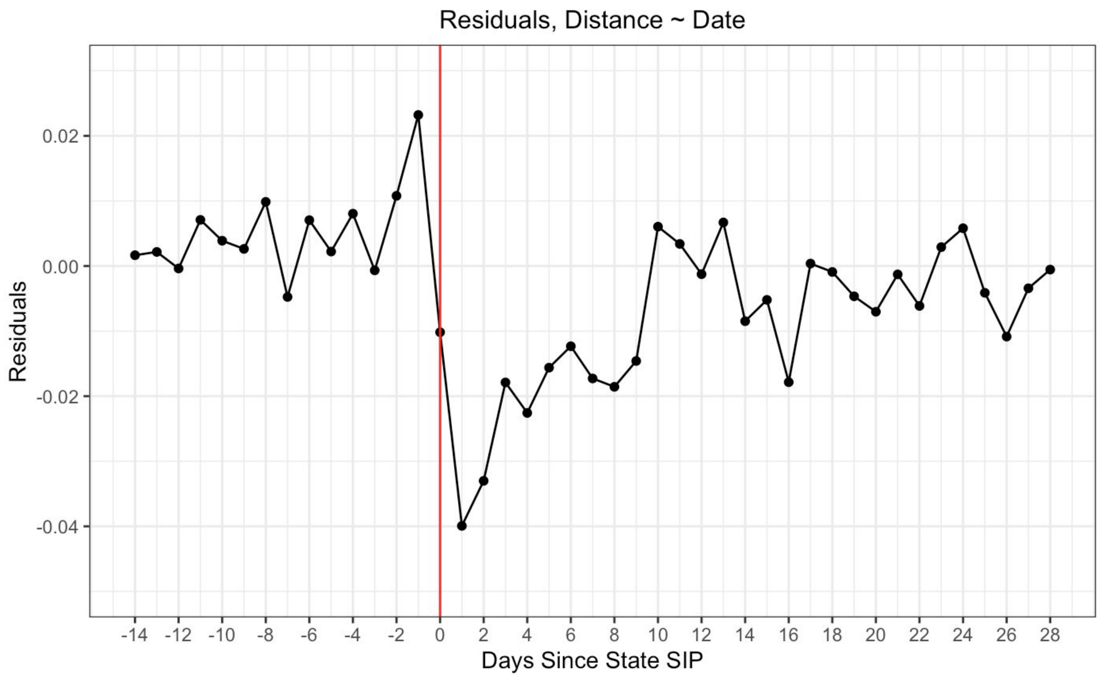


Figure 3 demonstrates the coefficient value on each relative date dummy variable. (Appendix A also includes a regression table with the coefficients for this model, as well as graphs and tables for several similar models run as robustness checks.) While Figure 2 demonstrates a notable pre-SIP downward trend in mobility, this analysis confirms that there is a significant increase in movement over a three day period before statewide orders are put in place, followed by a noticeable drop in average distance traveled between the day before the SIP order (pre_sip_1) and the day after the SIP order (post_sip_1). This localized effect seems to disappear within a 10-day window of time.

Finally, to further parse out the effects of state-level policies from a national downward trend in average distance traveled, we regress average distance traveled by county on date in the panel, and plot the residuals by day relative to the state SIP. These residuals demonstrate behavior in each state that eventually has a SIP, compared to national trends on a given calendar day.

Figure 4: Average Residuals of Change in Distance Traveled by Relative Date



In Figure 4 above, an average residual value of zero represents a reduction in movement that aligns with the national average on that calendar day. Before statewide SIP orders, the average residual value hovers within 1 percentage point of 0, indicating that states are largely following national trends. Interestingly, as previously confirmed, we see a spike in average distance traveled in the day directly preceding statewide SIP orders, followed by a reduction of ~6 percentage points by the day after SIP orders are in effect. This apparent reduction gradually disappears between Days 2 and 10, until counties re-align with national trends. This finding suggests that SIP orders have a small yet noticeable impact in the short-term, but that they are not likely to be driving national social distancing patterns.

Based only on anecdotal observations among our own communities, we believe that the small spike in movement directly preceding the SIP order is likely due to the desire to gather supplies or make other arrangements before the SIP is enacted. In most states, the SIP order was announced in advance of its enactment. For example, Illinois governor J.B. Pritzker announced on the afternoon of Friday, March 20 that the state's SIP order would be enacted the next afternoon at 5:00 pm.[7] Perhaps people responded to this announcement by traveling to grocery stores or pharmacies to collect supplies before staying home.

To ensure that this observed effect is not due to a specific idiosyncrasy in the distance-traveled variable, we use the same regression model to test a different outcome variable that can also be used to measure social movement. Figure 5 below shows the event study regression coefficients using a different mobility outcome measure from UNACAST. This variable measures change of visits to non-essential retail and

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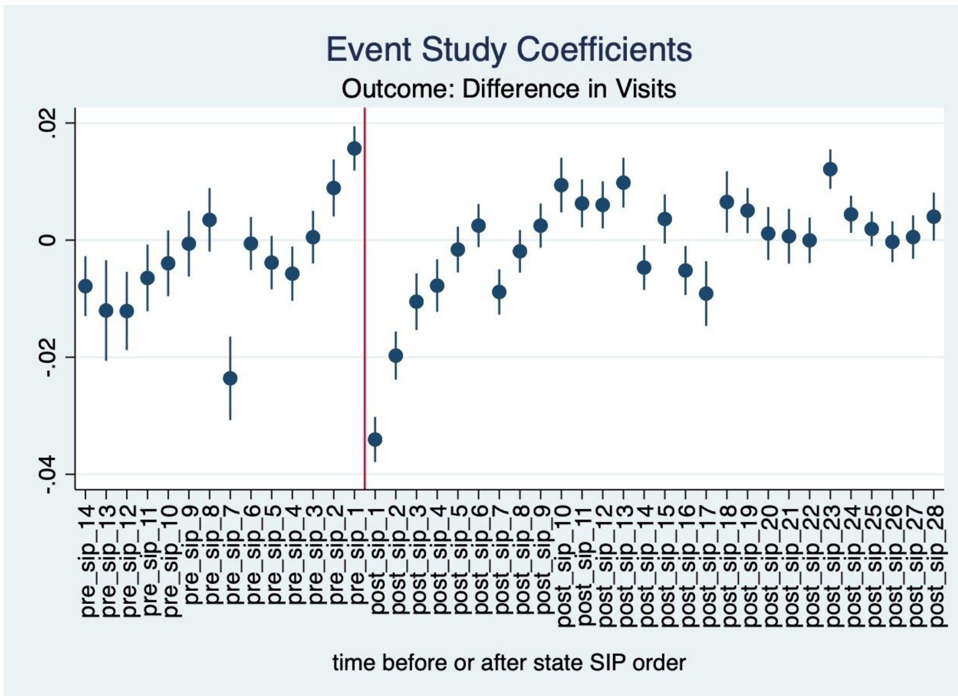
7 https://www.chicagotribune.com/coronavirus/ct-coronavirus-illinois-shelter-in-place-lockdown-order-20200320-teedakbfw5gvdgmnaxlel54hau-story.html

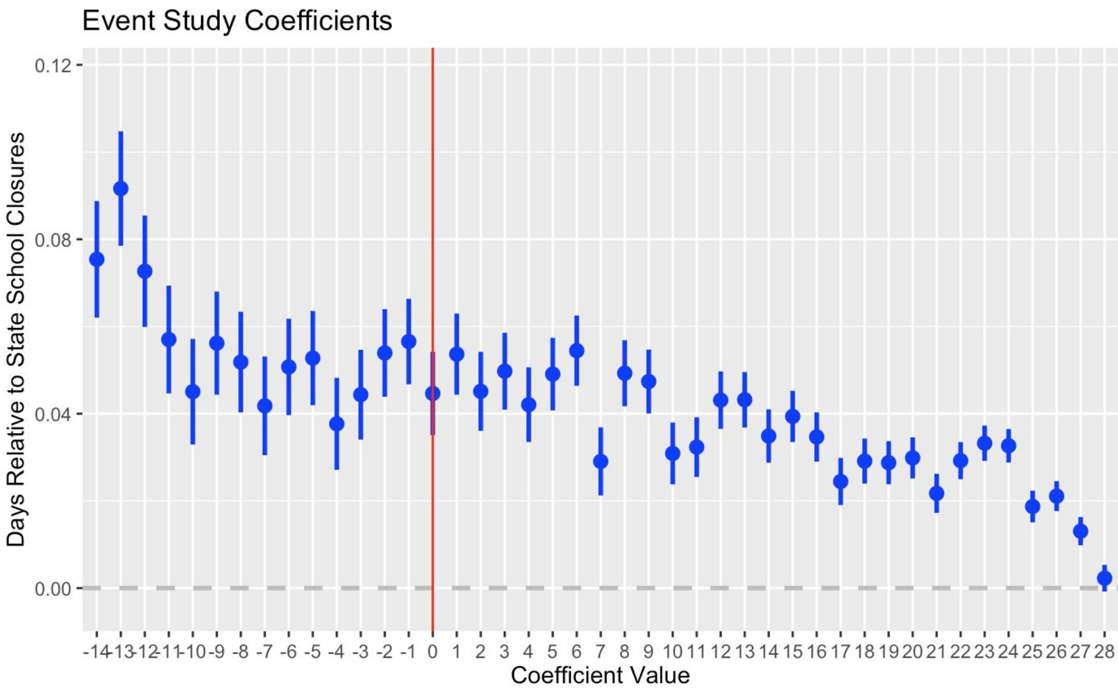
services. Again, this variable is expressed as a daily percentage of the average number of visits on the same day of the week during the pre-COVID-19 baseline time period. You can see that a similar pattern persists using this outcome variable.

Figure 5: Event Study Coefficients Before and After Statewide SIP Order, Difference in Visits



It is important to note, however, that this observed effect of the statewide SIP policy does not necessarily extend to all statewide policies aimed at reducing social contact. All states closed public schools to slow the spread of COVID-19. So, we also conduct a similar event study analysis on the distance-traveled variable, focussing the analysis around the date that each state closed schools. Figure 6 shows the coefficients from this analysis. There is not an obvious change in mobility behavior around the date of statewide school closures.

Figure 6: Event Study Coefficients Before and After Statewide School Closures



VI. Conclusion

The goal of our analysis was to explore the impact of state-level shelter-in-place (SIP) orders on individual movement throughout the COVID-19 pandemic, using publicly available mobility data. States that enacted SIP policies in March and April of 2020 did so to reduce social contact and slow the spread of the disease. We used measures of movement from cell phone tracking data to understand whether Americans altered their typical travel and movement habits in response to these orders. On average, Americans began to reduce their movement patterns many days before their state's official SIP policy was enacted, so we do recognize that most of the change in mobility cannot be attributed to the SIP orders.

We leveraged an event study regression model to examine whether statewide SIP policies had an effect in the days immediately before and after policies were enacted. We found a small but significant increase in average movement in the days immediately preceding the enactment of a statewide SIP, followed by a decrease in average movement that persists for about ten days following the SIP order. This finding suggests that SIP orders did have a relatively small and short-term effect on mobility.

One data quality concern is the baseline that UNACAST uses to calculate the variables that we analyzed. Ideally, we would calculate the baseline for a given day by averaging data from that same day of the week and the same month across multiple years. Instead, UNACAST creates a baseline for each day of the week based on just a few weeks before COVID-19 responses began in the U.S. If data were available for several prior years, we would repeat this analysis using a more trustworthy benchmark. Furthermore, it is important to note that in this paper, we only explore the effects of statewide SIP orders enacted by U.S. state governors and their respective administrations. Based on our preliminary analysis of similar orders at other levels of government, we are not confident that this effect can be generalized to similar orders enacted at the local or federal levels.

With additional time, there are several additional model specifications that would be worth exploring. Specifically, we would be interested in interacting demographic variables with the number of days relative to a statewide SIP order, to better understand additional factors that might be driving differences in behavior. To verify consistency between mobility datasets, we are interested in leveraging an outcome indicator from Google's publicly available mobility data, such as time spent in residences. While data sources on other types of policy responses at the state and county levels are often incomplete, we would be interested in supplementing these datasets and exploring the effects of park closures, workplace closures, and limits on public gatherings on mobility. We could adapt our models to explore behavior change as states begin to lift their restrictions. Additionally, we would like to assess the effects of state SIP policies on cases and deaths, as well as the relationship between mobility and health outcomes.

Nevertheless, we hope that our current findings will help to inform state-level public health and public policy responses to anticipated COVID-19 resurgences over the coming months.

APPENDIX A: Variations on Event Study Regression Models

We recognize that reasonable people might disagree on the exact specifications that we should include in an event study regression. To test our findings for robustness, we run several regression models that are similar to, but slightly different from, the one described in the body of this paper. For all of the regression models below, the outcome is the difference in distance traveled compared to the pre-COVID baseline. Model 1 is the model described in the body of the paper. The graph is replicated here for reference. Models 4-5 are variations on that model (as described in the subtitle of each coefficient graph). We observe similar trends in each of these models (especially the difference between the day before and the day after the SIP order), which suggests that our findings are robust.

Figure A-1: Event Study Regression Coefficients (Variations on Model)

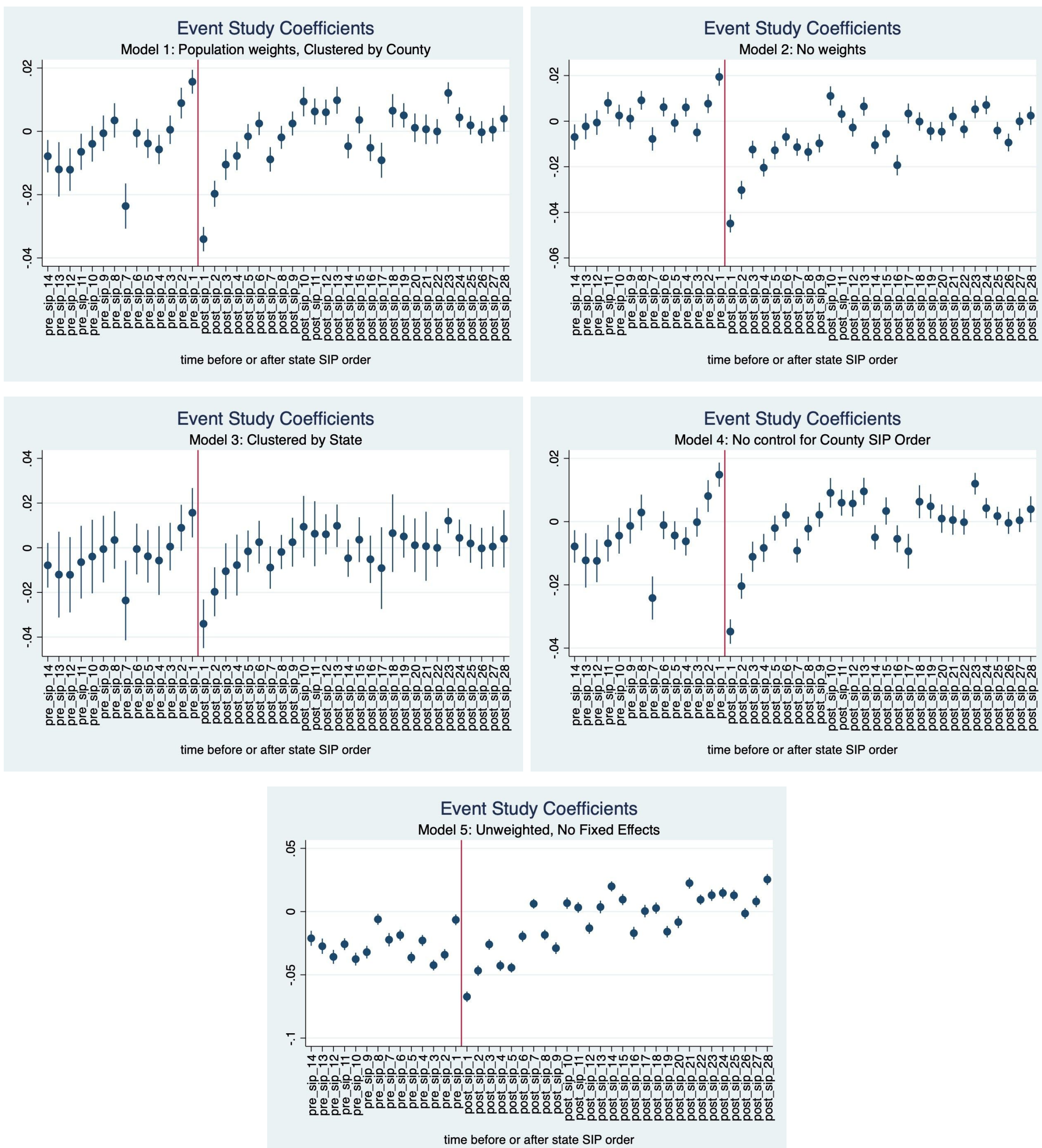


Table A-1: Coefficients for Event Study Regressions

	Model 1	Model 2	Model 3	Model 4	Model 5
		no weights	*clustered by state*	*no control for local SIP order*	*no fixed effects*
pre_sip_14	-0.00785**	-0.00695*	-0.00785	-0.00784**	-0.0211***
	(-3.01)	(-2.46)	(-1.58)	(-3.00)	(-6.96)
pre_sip_13	-0.0120**	-0.00228	-0.0120	-0.0123**	-0.0274***
	(-2.74)	(-0.79)	(-1.26)	(-2.80)	(-8.88)
pre_sip_12	-0.0121***	-0.000624	-0.0121	-0.0124***	-0.0358***
	(-3.55)	(-0.23)	(-1.44)	(-3.61)	(-12.74)
pre_sip_11	-0.00646*	0.00802**	-0.00646	-0.00684*	-0.0258***
	(-2.22)	(3.29)	(-0.80)	(-2.32)	(-10.86)
pre_sip_10	-0.00395	0.00248	-0.00395	-0.00443	-0.0376***
	(-1.38)	(1.02)	(-0.48)	(-1.53)	(-14.50)
pre_sip_9	-0.000606	0.00112	-0.000606	-0.00135	-0.0320***
	(-0.21)	(0.47)	(-0.08)	(-0.47)	(-12.61)
pre_sip_8	0.00346	0.00914***	0.00346	0.00289	-0.00609**
	(1.25)	(4.35)	(0.54)	(1.00)	(-2.74)
pre_sip_7	-0.0236***	-0.00779**	-0.0236*	-0.0242***	-0.0222***
	(-6.48)	(-2.98)	(-2.66)	(-6.95)	(-8.22)
pre_sip_6	-0.000576	0.00617**	-0.000576	-0.00111	-0.0186***
	(-0.25)	(2.94)	(-0.10)	(-0.49)	(-8.48)
pre_sip_5	-0.00384	-0.000774	-0.00384	-0.00438	-0.0364***
	(-1.65)	(-0.37)	(-0.65)	(-1.90)	(-16.03)
pre_sip_4	-0.00573*	0.00606**	-0.00573	-0.00624**	-0.0229***
	(-2.42)	(2.92)	(-0.75)	(-2.73)	(-10.32)
pre_sip_3	0.000507	-0.00495*	0.000507	-0.000174	-0.0424***
	(0.22)	(-2.36)	(0.10)	(-0.07)	(-19.82)

pre_sip_2	0.00891***	0.00767***	0.00891	0.00809**	-0.0341***
	(3.60)	(3.63)	(1.73)	(3.16)	(-15.15)
pre_sip_1	0.0157***	0.0194***	0.0157**	0.0149***	-0.00650**
	(8.13)	(9.79)	(2.85)	(7.63)	(-3.02)
post_sip_1	-0.0341***	-0.0449***	-0.0341***	-0.0348***	-0.0673***
	(-17.33)	(-22.35)	(-6.29)	(-17.61)	(-32.16)
post_sip_2	-0.0197***	-0.0302***	-0.0197***	-0.0204***	-0.0467***
	(-9.41)	(-14.80)	(-3.62)	(-9.93)	(-22.16)
post_sip_3	-0.0105***	-0.0124***	-0.0105	-0.0111***	-0.0259***
	(-4.26)	(-6.37)	(-1.69)	(-4.57)	(-12.03)
post_sip_4	-0.00777***	-0.0204***	-0.00777	-0.00831***	-0.0428***
	(-3.40)	(-10.29)	(-1.14)	(-3.68)	(-20.24)
post_sip_5	-0.00160	-0.0128***	-0.00160	-0.00205	-0.0443***
	(-0.80)	(-6.29)	(-0.35)	(-1.02)	(-22.60)
post_sip_6	0.00248	-0.00689***	0.00248	0.00212	-0.0196***
	(1.33)	(-3.36)	(0.52)	(1.13)	(-8.95)
post_sip_7	-0.00885***	-0.0114***	-0.00885	-0.00917***	0.00617**
	(-4.50)	(-5.89)	(-1.87)	(-4.76)	(3.18)
post_sip_8	-0.00190	-0.0135***	-0.00190	-0.00221	-0.0184***
	(-1.03)	(-6.61)	(-0.50)	(-1.15)	(-8.94)
post_sip_9	0.00247	-0.00971***	0.00247	0.00217	-0.0289***
	(1.28)	(-4.76)	(0.45)	(1.11)	(-12.31)
post_sip_10	0.00940***	0.0111***	0.00940	0.00911***	0.00670**
	(3.95)	(5.15)	(1.37)	(3.82)	(2.93)
post_sip_11	0.00627**	0.00312	0.00627	0.00599**	0.00324
	(3.00)	(1.59)	(0.86)	(2.87)	(1.51)
post_sip_12	0.00602**	-0.00278	0.00602	0.00575**	-0.0131***
	(2.94)	(-1.36)	(1.35)	(2.74)	(-5.79)

post_sip_13	0.00982***	0.00647**	0.00982*	0.00957***	0.00364
	(4.53)	(3.10)	(2.07)	(4.37)	(1.43)
post_sip_14	-0.00469*	-0.0105***	-0.00469	-0.00495*	0.0199***
	(-2.41)	(-5.29)	(-1.13)	(-2.52)	(9.83)
post_sip_15	0.00361	-0.00553**	0.00361	0.00336	0.00954***
	(1.68)	(-2.60)	(0.72)	(1.53)	(4.26)
post_sip_16	-0.00518*	-0.0193***	-0.00518	-0.00544*	-0.0170***
	(-2.43)	(-8.47)	(-0.98)	(-2.50)	(-6.70)
post_sip_17	-0.00913**	0.00336	-0.00913	-0.00937***	0.000400
	(-3.24)	(1.51)	(-1.00)	(-3.35)	(0.16)
post_sip_18	0.00652*	-0.000168	0.00652	0.00630*	0.00276
	(2.44)	(-0.08)	(0.75)	(2.37)	(1.22)
post_sip_19	0.00505*	-0.00431*	0.00505	0.00485*	-0.0159***
	(2.57)	(-2.12)	(1.07)	(2.47)	(-6.84)
post_sip_20	0.00113	-0.00461*	0.00113	0.000956	-0.00828***
	(0.49)	(-2.14)	(0.19)	(0.42)	(-3.40)
post_sip_21	0.000661	0.00204	0.000661	0.000501	0.0225***
	(0.28)	(0.94)	(0.09)	(0.21)	(10.15)
post_sip_22	-0.0000307	-0.00356	-0.0000307	-0.000173	0.00942***
	(-0.02)	(-1.81)	(-0.01)	(-0.09)	(4.65)
post_sip_23	0.0121***	0.00522**	0.0121***	0.0120***	0.0130***
	(7.03)	(2.58)	(4.36)	(6.87)	(5.66)
post_sip_24	0.00441**	0.00709***	0.00441	0.00427**	0.0147***
	(2.72)	(3.44)	(1.08)	(2.62)	(6.62)
post_sip_25	0.00191	-0.00411*	0.00191	0.00178	0.0129***
	(1.27)	(-2.13)	(0.45)	(1.18)	(5.92)
post_sip_26	-0.000283	-0.00938***	-0.000283	-0.000398	-0.00150

	(-0.16)	(-4.75)	(-0.06)	(-0.22)	(-0.69)
post_sip_27	0.000527	-0.0000635	0.000527	0.000431	0.00799***
	(0.28)	(-0.03)	(0.12)	(0.23)	(3.47)
post_sip_28	0.00401	0.00243	0.00401	0.00392	0.0254***
	(1.92)	(1.17)	(0.63)	(1.89)	(11.33)
county_sip	-0.00471*	-0.0231***	-0.00471		-0.00957***
	(-2.22)	(-7.92)	(-1.99)		(-5.41)
mlag_1	0.381***	0.207***	0.381***	0.381***	0.425***
	(36.89)	(28.81)	(17.82)	(37.24)	(57.30)
mlag_2	0.0704***	0.0751***	0.0704***	0.0707***	0.0908***
	(11.73)	(17.36)	(6.15)	(11.75)	(18.55)
mlag_3	0.0503***	0.0510***	0.0503***	0.0508***	-0.0127**
	(8.16)	(11.20)	(5.30)	(8.33)	(-2.81)
mlag_4	0.0391***	0.0362***	0.0391***	0.0397***	0.00404
	(8.84)	(8.48)	(4.43)	(9.09)	(0.96)
mlag_5	0.0159**	0.0365***	0.0159	0.0168**	0.0838***
	(2.63)	(7.85)	(1.38)	(2.71)	(16.19)
mlag_6	0.127***	0.0792***	0.127***	0.128***	0.257***
	(21.41)	(14.27)	(13.08)	(21.58)	(45.10)
_cons	-0.121***	-0.141***	-0.121***	-0.121***	-0.0429***
	(-28.92)	(-48.42)	(-13.64)	(-29.50)	(-36.98)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
t statistics in parentheses

APPENDIX B: State-Specific Analyses

Figure B-1: Difference in Distance Traveled from the Baseline
For every state with a statewide SIP order

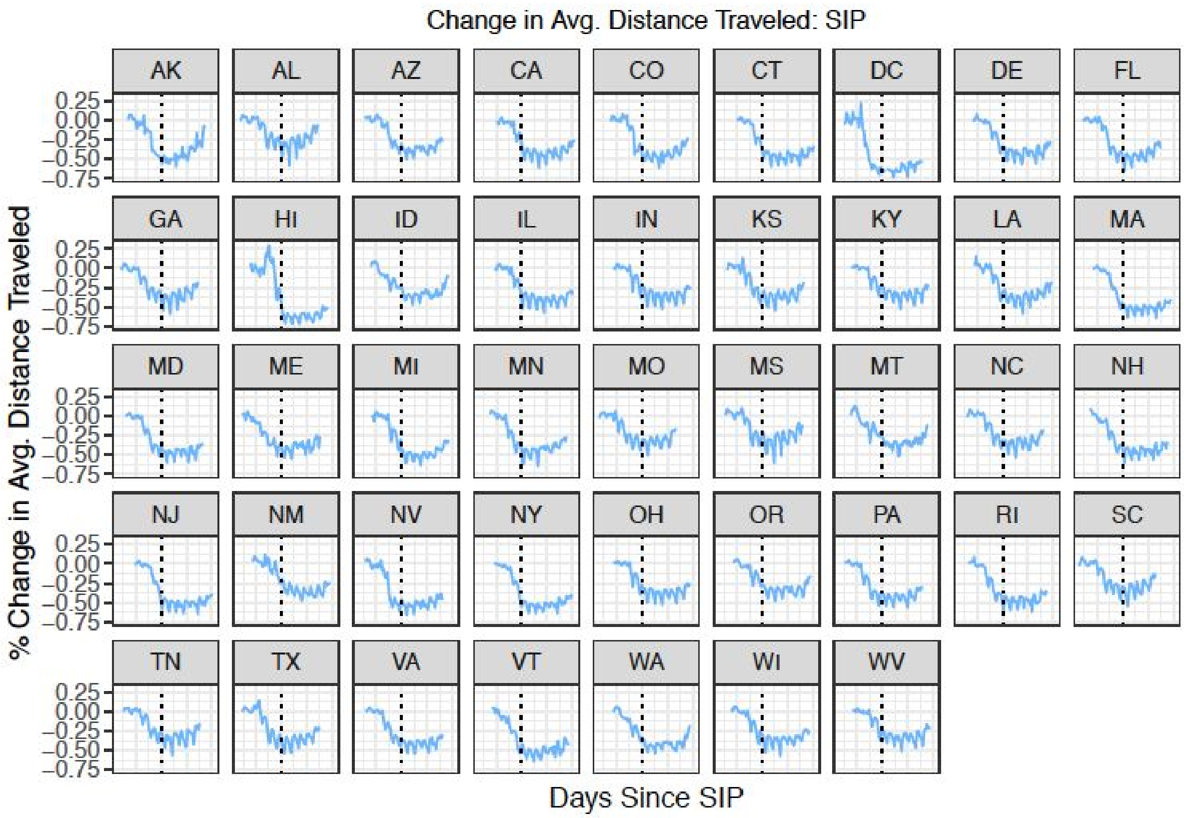
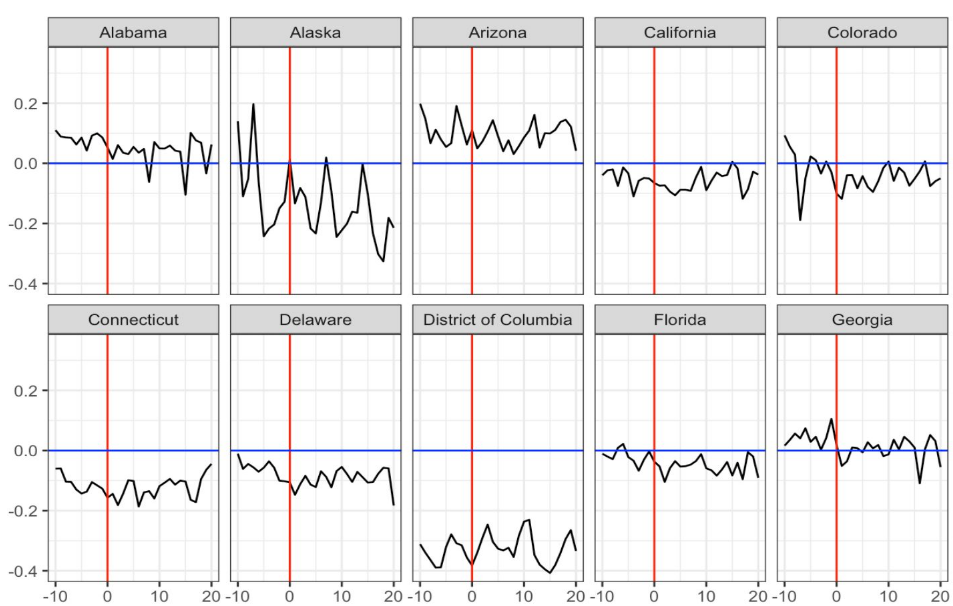
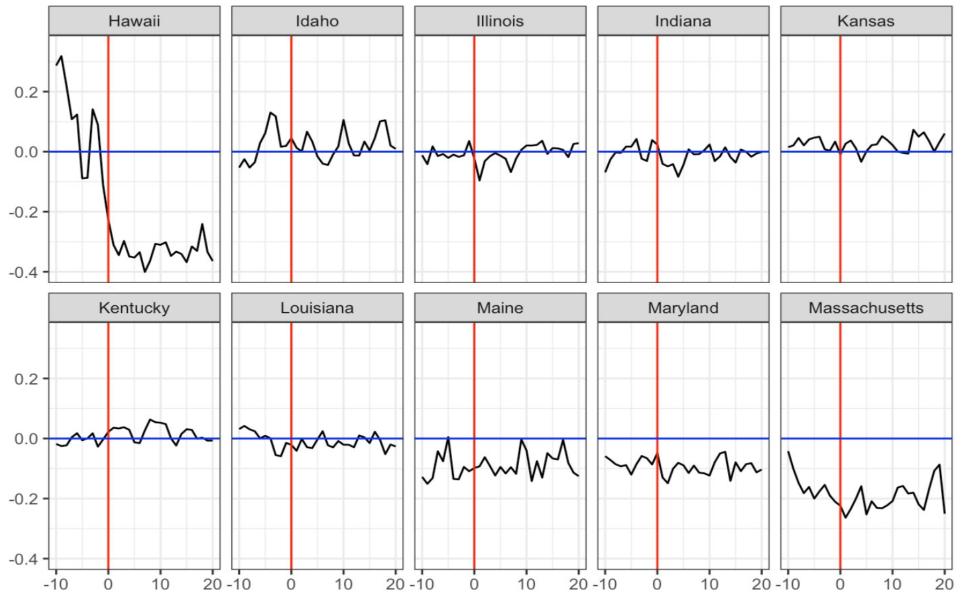
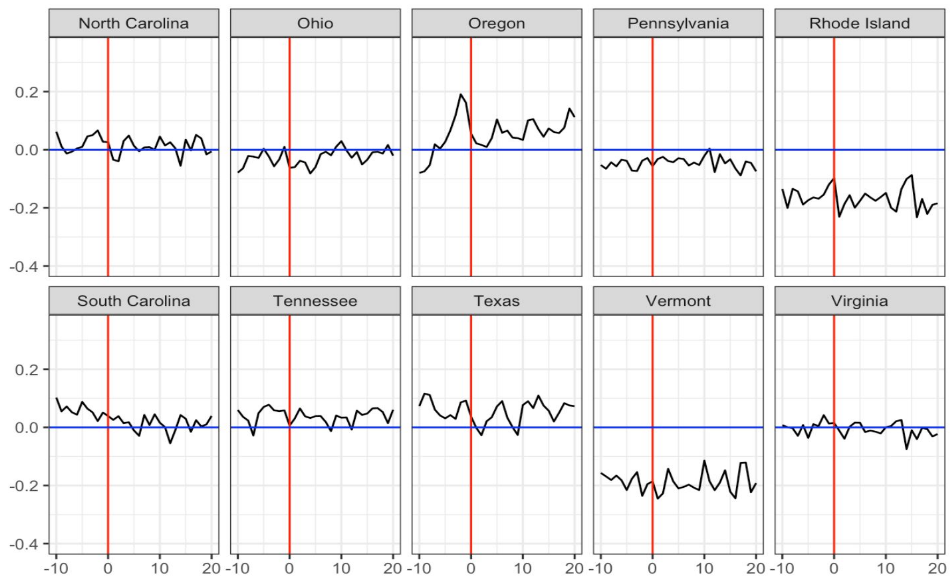
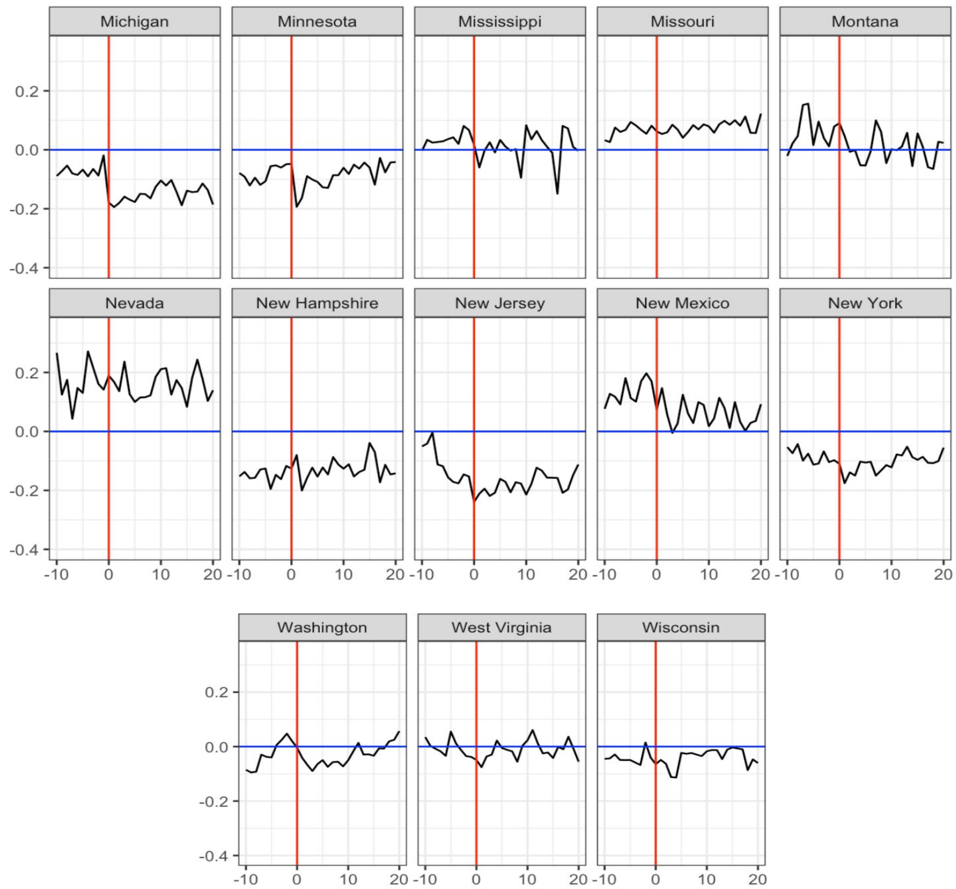


Figure B-2: Average Residuals of Change in Distance Traveled by Relative Date
For every state with a statewide SIP order




Hawaii
Idaho
Illinois
Indiana
Kansas
Kentucky
Louisiana
Maine
Maryland
Massachusetts
0.2
0.0
-0.2
-0.4
-10
0
10
20


North Carolina
Ohio
Oregon
Pennsylvania
Rhode Island
South Carolina
Tennessee
Texas
Vermont
Virginia
0.2
0.0
-0.2
-0.4
-10
0
10
20


Michigan
Minnesota
Mississippi
Missouri
Montana
Nevada
New Hampshire
New Jersey
New Mexico
New York
Washington
West Virginia
Wisconsin
0.2
0.0
-0.2
-0.4
-10
0
10
20