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ABSTRACT

When Do Shelter-In-Place Orders Fight COVID-19 Best? Policy Heterogeneity across States and Adoption Time*

Shelter in place orders (SIPOs) require residents to remain home for all but essential activities such as purchasing food or medicine, caring for others, exercise, or traveling for employment deemed essential. Between March 19 and April 20, 2020, 40 states and the District of Columbia adopted SIPOs. This study explores the impact of SIPOs on health, with particular attention to heterogeneity in their impacts. First, using daily state-level social distancing data from SafeGraph and a difference-in-differences approach, we document that adoption of a SIPO was associated with a 5 to 10 percent increase in the rate at which state residents remained in their homes full-time. Then, using daily state-level coronavirus case data collected by the Centers for Disease Control and Prevention, we find that approximately three weeks following the adoption of a SIPO, cumulative COVID-19 cases fell by 44 percent. Event-study analyses confirm common COVID-19 case trends in the week prior to SIPO adoption and show that SIPO-induced case reductions grew larger over time. However, this average effect masks important heterogeneity across states — early adopters and high population density states appear to reap larger benefits from their SIPOs. Finally, we find that statewide SIPOs were associated with a reduction in coronavirus-related deaths, but estimated mortality effects were imprecisely estimated.

JEL Classification: H75, I18

Keywords: coronavirus, COVID-19, shelter-in-place order, social distance

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1. Motivation

The SARS-CoV-2 virus, which causes the disease COVID-19, has spread rapidly within the United States. The total number of confirmed cases in the United States on March 12, 2020 was 1,629 which grew to 18,747 confirmed cases within seven days (Center for Disease Control and Prevention 2020a). The primary strategy suggested by governments worldwide to reduce the spread of COVID-19 is social distancing (Australian Government Department of Health. 2020; Public Health England. 2020; Public Health Agency of Canada. 2020; White House 2020). As of April 2, 2020, over 90 countries worldwide, representing half of the world's population, have requested or ordered their citizens to stay at home (Sandford 2020). In the United States, the most common comprehensive social distancing policy adopted is a shelter-in-place order (SIPO). A state SIPO requires residents to remain in their homes for all but essential activities such as purchasing food or medicine, caring for others, exercise, or traveling for employment deemed essential.

The authority to issue SIPOs rests with state and local officials. While agencies of the Federal government (i.e. the Centers for Disease Control and Prevention) or the Executive Branch can make recommendations on social distancing to state and local officials, the authority to place a state under a SIPO is left to its governor. In some cases, sub-state local jurisdictions, i.e. counties, cities, and townships, also have the authority to issue SIPOs through orders from mayors, County Public Health Department officials, and other local government entities.[1]

The first statewide SIPO was announced by Governor Gavin Newsom of California on March 19, 2020. Following the adoption of the California order, between March 20, 2020 and

[1] For example, Austin, Texas and Denver, Colorado (among many other municipalities) put in place municipal SIPOs when there was no state-level SIPO in place at the time.

April 19, 2020, 39 additional states and the District of Columbia enacted similar statewide SIPOs.[2]

Enforcement of SIPOs is handled at the local level via law enforcement agencies (Napoleon 2020; Fracassa 2020; Caswell 2020), though warnings for failure to comply with a SIPO are very common for first offenses (Barr 2020). However, in contrast to a shelter-in-place advisory (Commonwealth of Massachusetts 2020) or a gubernatorial recommendation (Herbert 2020), SIPOs have the weight of state law behind them. Violating a SIPO is considered a misdemeanor (Allday 2020; Martineau 2020). Punishments vary from state to state, but generally take the form of a fine or, if repeated, a prison term. For example, in Maryland, those who willfully violate the state's shelter-in-place order are subject to a fine of $5,000 and up to one year of imprisonment (Maryland Executive Order 20-03-30-01 2020). To take another example, in Minnesota, individuals are subject to fines up to $1,000, and imprisonment for no more than 90 days (Minnesota Executive Order 20-20 2020). Still, social pressures appear to play a very important role in SIPO compliance (Ronayne and Thompson 2020).[3]

Numerous reports from national, state, and local media sources suggest a substantial reduction in public gatherings following SIPOs (Hermann 2020; Fry 2020) as well as business closings (Arnold 2020; Cox 2020; U.S. Department of Labor 2020). However, these associations may be explained in whole, or in part, by voluntary social distancing in response to health knowledge that predated and, perhaps, drove SIPO adoption. Emerging evidence by economists that has sought to isolate the causal impact of SIPOs on social distancing points to

[2] As of April 15, 2020, 6 states issued limited orders that closed non-essential businesses, and 2 states enacted targeted shelter-in-place orders that applied only to those ages 65 and older and who had underlying health conditions (Mervosh et al. 2020; Weaver 2020).

[3] Media reports suggest that some private citizens have begun to monitor neighbors' behavior and local businesses, reporting perceived violations of SIPOs to local law enforcement agencies (Webber 2020).

modest short-run effects from statewide orders (Friedson et al. 2020; Gupta et al. 2020: Abouk and Heydari 2020), with larger effects for county policies (Gupta et al. 2020).

A rapidly emerging literature has begun to study the short-run health effects of SIPOs. Friedson et al. (2020) focus specifically on California, which enacted the nation's first shelter-in-place order. The authors argue that because California is a high-urbanicity, high-population density state that implemented a SIPO during a period of relatively low coronavirus case growth, it was uniquely positioned to reap important short-run health benefits. Using a synthetic control approach, and a variety of matching strategies, Friedson et al. (2020) find that California's SIPO was associated with approximately 125.5 to 219.7 fewer COVID-19 cases per 100,000 following the policy's first three weeks of enactment. To put their estimates in context of SIPO-related economic costs, they suggest that California's SIPO caused approximately 400 job losses per life saved.[4]

While understanding the California experience is important, the findings of Friedson et al. (2020) may not generalize to jurisdictions with lower population densities or that adopted SIPOs during periods of rapid community spread of coronavirus. As the authors note, California is an outlier, both as an early SIPO adopter and as a highly urbanized state with extraordinarily low COVID-19 case growth at the time of SIPO adoption. Given that an additional 40 states (including D.C.) adopted statewide SIPOs following California's enactment, this question is ripe for investigation

First, using daily state-level measures of social mobility from SafeGraph, Inc., we document that statewide SIPOs were associated with a 5 to 10 percent increase (relative to the

[4] While primarily focusing on mobility responses to SIPOs, Gupta et al. (2020) extensively discuss the empirical challenges associated with estimating the health impacts of SIPOs. They find evidence that states enacting SIPOs may do so in periods of rapid local coronavirus case growth. Failure to adequately explore endogenous policy adoption may positively bias estimated treatment effects.

pre-treatment period) in the share of the population that sheltered in place completely on any given day. This treatment-control differential increases during the first week following SIPO adoption and then remains constant or slightly declines. Next, turning to COVID-19, difference-in-differences estimates show that the adoption of a SIPO had little effect on COVID-19 cases during the five (5) days following its enactment, corresponding to the median incubation period. However, after the incubation period, and intensifying rapidly three weeks or more after the policy's adoption, SIPO adoption is associated with an up to 43.7 percent decline in COVID-19 cases. Approximately 3 to 4 weeks following SIPO adoption, this corresponds to approximately 2,510 fewer cumulative COVID-19 cases for the average SIPO-adopting state.[5] Evidence from event study analyses is consistent with common pre-treatment trends. Our results persist when we (i) drop California from our panel, confirming that we are not simply replicating Friedson et al. (2020), and (ii) when we control for state-specific growth in COVID-19 testing, which could affect the number of reported coronavirus cases. While statewide SIPOs were negatively related to coronavirus-related deaths, but estimated mortality effects were imprecisely estimated.

Importantly, we find that the impact of the average state SIPO masks important state-level heterogeneity. The earliest adopters of statewide SIPOs saw the largest declines in the rate of coronavirus cases, including declines in the rate of COVID-19-related mortality. In addition, more densely populated states also appear to reap relatively larger health benefits from their SIPOs. Consistent with these larger health impacts, we find that statewide SIPOs are far more effective at increasing social distancing among early adopting states and states with higher population densities. We conclude that there are important heterogeneous health impacts of statewide SIPOs across states and adoption time.

[5] The mean number of cumulative cases of coronavirus in the average SIPO-adopting state over our sample period was 5,744 (for the full sample, this number was 5,501).

2. Background

After being detected in Wuhan, China, in December 2019, the first confirmed case of COVID-19 in the United States was identified on January 21, 2020 in Washington State.[6] The disease spread exponentially over the next three months across the U.S., with confirmed cases at 778,328 as of April 20, 2020, accounting for 32 percent of the global caseload. Public health interventions to flatten this growth trajectory have mobilized around two complementary sets of policy responses.[7] Surveillance-based policies, such as expanding COVID-19 testing capacity and deploying antibody tests, seek to monitor the spread and intensity of the disease (Gupta et al. 2020).[8] These efforts can be instrumental in identifying infected persons, and tracing and monitoring their contacts to limit further spread of the virus. In addition, mitigation and suppression policies aim at lowering the reproduction rate of the virus and slowing its spread by limiting interactions between individuals in the community and increasing social distancing (Ferguson et al. 2020). Components of such a response include shelter-in-place orders, closures of educational facilities, restrictions on mass gatherings, and closure of business and non-essential services.

Given that the authority for imposing sheltering-at-home orders and school or businesses closures rests with states and localities, the Federal response has focused on (i) providing funding to states to bolster preparedness and healthcare capacity, and (ii) surveillance-based policies aimed at expanding testing and tracking infection rates. Some suppression efforts have

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[6] See: https://www.cdc.gov/media/releases/2020/p0121-novel-coronavirus-travel-case.html.
[7] While numerous clinical trials for a COVID-19 vaccine and anti-viral treatments are underway, significant lag times with clinical testing and approval by the Food and Drug Administration (FDA) mean that an effective prophylactic and treatment are unlikely over the short-term. Hence, public health efforts centered on suppression and mitigation take on added relevance to prevent the surge in cases from overwhelming the healthcare system.
[8] Also see: https://www.cdc.gov/coronavirus/2019-ncov/covid-data/covidview/purpose-methods.html.

also included travel restrictions to limit infections from international exposure. For example, on January 31, 2020, the Trump administration enacted restrictions on all foreign nationals who had been in China over the past 14 days from entering the U.S. Then, following a surge in COVID-19 related deaths, the administration suspended travel from the Schengen Area to the U.S. starting on March 13, which was further extended to include the U.K. and Ireland three days later.[9] A global health advisory, advising U.S. citizens to avoid all international travel, was issued by the State Department on March 31. Also, the Centers for Disease Control and Prevention (CDC) has issued further guidelines for social distancing and personal protective measures (face covering, hand-washing, etc.) as part of a broader strategy for community mitigation while awaiting a vaccine or effective treatment.

A flurry of responses at the state and local levels also ensued. At the local level, one of the first actions taken by many jurisdictions was to declare a state of emergency, which typically frees up the state's office of emergency management to deploy resources to localities for immediate assistance.[10] The power for imposing the strongest mitigation and suppression policies lies with state and local authorities. Consequently, following the declaration of emergency, many states and jurisdictions started closing schools and shutting down non-essential businesses and services.

The first shelter-in-place order was simultaneously imposed by health authorities on March 17, in the San Francisco Bay Area (Alameda, Contra Costa, Marin, San Mateo, and Santa Clara counties, and the cities of San Francisco and Berkeley). Two days later, on March 19, 2020, Governor Gavin Newsom ordered the first statewide shelter-in-place order in California.

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[9] See: https://travel.state.gov/content/travel/en/traveladvisories/presidential-proclamation--travel-from-europe.html.
[10] President Trump declared a National Emergency concerning the COVID-19 outbreak, on March 13.

Following CA's SIPO, 40 states and D.C. issued SIPOs of their own.[11] Additionally, several cities and counties issued their own shelter-in-home order even if there was no statewide order; for instance, as of April 20, 2020, more than 50 percent of the population in Utah is covered under orders issued by Davis county, Salt Lake county, and Summit county despite no statewide order in place.

Transmission of COVID-19 is presently believed to occur via respiratory droplets, usually emitted during coughing, sneezing, or nose-blowing (Centers for Disease Control and Prevention 2020a, World Health Organization 2020c & 2020d) and possibly also through normal breathing function in close proximity to an infected person (Fineberg 2020). In light of this, the primary pathway through which a shelter-in-place order can potentially mitigate and suppress the spread of COVID-19 is by restraining close contact between persons. If SIPOs effectively promote greater social distancing, then this should translate into a reduction in the number of reported cases and deaths as disease transmission slows.[12] However, reductions in new cases and deaths should occur with a lag given that the incubation period for COVID-19 is 2 to 14 days (Centers for Disease Control and Prevention 2020b, Li et al. 2020)[13] and time from first symptoms to acute respiratory distress syndrome (ARDS), which is strongly associated with mortality from COVID-19, may take up to an additional 8 days (Wang et al. 2020, Wu et al. 2020, Zhou et al. 2020).[14]

Other indirect behavioral pathways may also explain a link between SIPOs and coronavirus-related cases and deaths. For instance, SIPOs may affect confirmed cases by

[11] States generally include some exceptions to shelter-in-place orders, including going to work for certain jobs, grocery shopping, walking the dog, exercising, or getting medical care.
[12] There is, in fact, important work showing that increased generosity of sick leave pay, which encourages social distancing, reduces the spread of contagious disease (Pichler and Ziebarth 2017; Pichler et al. 2020).
[13] The incubation lag is 5 days at the median, and 10 days at the 97.5 percentile.
[14] Some transmission from asymptomatic infected persons during this period is also possible.

affecting selection into testing. Attempting to comply with the stay-at-home order or because of fear of getting exposed at medical facilities, infected persons who are unaware of their status may choose not to seek out medical care. Conditional on infection, SIPOs may also affect coronavirus-related mortality by reducing the demand for non-essential or elective medical procedures, thereby freeing up resources for care of COVID-19 patients.

This discussion underscores several key points that guide our empirical analyses. First, the incubation period for the virus and the lag from presentation of symptoms to acute respiratory distress imply important dynamics. SIPOs would not be expected to immediately dampen the growth curve given these dynamics, and strong effects may take some time to materialize (> 5 days for cases, and perhaps at least 14 days for deaths). Second, given that the effectiveness of SIPOs is driven by an increase in social distancing, this effectiveness may be moderated by factors such as urbanicity and population density that play in integral role in the spread of infections across communities. In other words, urbanicity and population density may serve as multipliers which can enhance the efficacy of a given level of social distancing. Third, given the exponential progression of infections, the effects of social distancing may magnify and accelerate over time if enacted early (Florida 2020; Friedson et al. 2020). This suggests that health benefits of SIPOs can vary depending on whether they were enacted early or late during the outbreak cycle. Our study provides among the first national evidence on the effectiveness of statewide shelter-in-home orders in promoting social distancing, in decreasing infection rates and coronavirus-related deaths, and potential heterogeneity in the response based on timing of enactment and state characteristics.

3. Data and Methods

3.1 Social Mobility Data

We begin our analysis by examining whether SIPOs affect social mobility, drawing daily state-level data on social distancing for the period March 8, 2020 to April 17, 2020 from SafeGraph, Inc. For our analysis, we leverage this firm's anonymized population movement dataset representing 45 million smartphone devices. These data have recently been used by the Centers for Disease Control and Prevention (CDC) to gather information on the degree to which social distancing has been practiced by individuals in the United States following the COVID-19 outbreak (Lasry et al. 2020). From these data we collect a state-by-day measure of the percent of the state population who remain at home for the entire day. A person's home is defined as a 153-meter by 153-meter area that receives the most frequent GPS pings during the overnight hours of 6pm to 7am. While this measure of social distancing is imperfect — for instance, it does not capture whether an individual engages in social distancing while outside the home — it is plausible to expect that having a higher percentage of the population who is "fully" sheltering in place is positively correlated with rates of social distancing.

Over our sample period, 35.7 percent of the population reported staying at home at all times (see Appendix Table 1). On average, 43.1 percent of individuals stayed at home on days when a state had a SIPO in place. This compares to 28.7 percent on state-days when a SIPO was not in effect.

3.2 Coronavirus Case and Mortality Data

Turning to our main analysis, we draw a panel of state-specific daily counts of COVID-19 cases from March 8, 2020 through April 20, 2020. These data are collected by the Centers for

Disease Control and Prevention (CDC) and made public by the Kaiser Family Foundation.[15] By April 20, 2020 there were a total of 778,328 positive screenings for COVID-19 in the United States. In Appendix Table 2, we show the day on which the first confirmed reported coronavirus case (and death) occurred in each state. The first known confirmed case was in Washington on January 21 followed by Illinois on January 24, though scientific knowledge on initial coronavirus arrival in the United States is evolving. The state with the last initial case of reported coronavirus was West Virginia on March 17. Deaths followed a similar pattern, with a lag, as expected from the coronavirus's incubation period (Lauer et al. 2020) and time from first symptom to acute respiratory distress syndrome (ARDS) (Wang et al. 2020). In Appendix Table 1, we show that the mean rate of coronavirus cases per 100,000 population over our analysis period was 45.9.

Figure 1 shows state-specific coronavirus case growth over our sample window. New York and New Jersey are clear outliers, on case growth trends that are higher than any other state. Over our sample period, the average increase in cases per 100,000 was about 8 times higher in New York and New Jersey as compared to the other 49 states (26.9 daily cases per 100,000 vs. 3.4 per 100,000). This is owed to the spread of COVID-19 in the high population density cities of New York City, Newark, and Jersey City (Rosenthal 2020; Warren 2020).

Figure 2 and Appendix Table 2 describe coronavirus-related mortality from March 8 through April 20. The average COVID-19 death rate was 1.6 per 100,000 population. Figure 2 suggests a delay in the growth of deaths, as compared to cases. Total deaths did not start rising (even in New York and New Jersey) until late March or early April. This lag is consistent with the time period from infection to death.

[15] See data available here: https://www.nytimes.com/interactive/2020/us/coronavirus-us-cases.html

3.3 Shelter-in-Place Orders

We collect statewide shelter-in-place orders from Mervosh et al. (2020) as well as from our own search of state orders.[16] Table 1 lists the set of SIPOs enacted over our sample period and Figure 3 shows maps depicting the geographic and temporal adoption of SIPOs. California was the first state to adopt a shelter in place order on March 19, 2020. Following California, the first cluster of states to adopt SIPOs was in the Midwest and parts of the Northeast, as well as Louisiana. Notably, many of these states were also in the midst of COVID-19 outbreaks during that time (Gupta et al. 2020). Later adopters of SIPOs were largely concentrated in the mid-Atlantic and upper Midwest.

As of April 20, 2020, 40 states and the District of Columbia had adopted statewide SIPOs. Among those states who had not adopted a SIPO, six (6) had adopted some *limited shutdown orders* that fell short of full SIPOs, including mandates to close non-essential businesses (Arkansas, Iowa, Kentucky, Massachusetts[17], North Dakota, and Wyoming), and more narrowly targeted SIPOs, which apply only to elderly individuals and those with underlying health conditions (Kentucky and Oklahoma). Only Nebraska, South Dakota, and Utah had not adopted a SIPO, a limited shutdown order, or a targeted SIPO.[18]

3.4 Methods

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[16] Mervosh et al. (2020)'s article is available at: https://www.nytimes.com/interactive/2020/us/coronavirus-stay-at-home-order.html

[17] The governor of Massachusetts did not issue a shelter-in-place order, but did offer a shelter-in-place advisory on March 24, 2020. However, this advisory did not carry the force of law.

[18] Notably, however, county shelter-in-place orders in Texas and Utah covered over half of the state population by March 25 and April 2, respectively.

Our main analysis sample uses a difference-in-differences regression design to estimate the association between state SIPOs and COVID-19 cases. Specifically, we estimate:

$$\ln(COVIDCASE_{st}) = \beta_0 + \beta_1 * SIPO\_1to5_{st} + \beta_2 * SIPO\_6to14_{st} + \beta_3 * SIPO\_15to19_{st} + \beta_4 * SIPO\_20plus_{st} + \beta_5 * LIMITORDER_{st} + \beta_6 * PARTORDER_{st} + \beta_7 * TRAVEL_{st} + \beta_8 * EMERG_{st} + \beta_9 * TEMP_{st} + \beta_{10} * PRECIP_{st} + \alpha_s + \gamma_t + \alpha_s * t + \varepsilon_{st} \quad (1)$$

where ln ($COVIDCASE_{st}$) is the natural log of the count of COVID-19 cases in state *s* on day *t*, $SIPO\_1to5_{st}$ is an indicator set equal to 1 for the period 1 to 5 days following a SIPO's adoption, $SIPO\_6to14_{st}$ an analogous indicator for the period 6 to 14 days following adoption, $SIPO\_15to19_{st}$ is also an analogous indicator for the period 15 to 19 days following adoption, and $SIPO\_20plus_{st}$ is a final analogous indicator for 20 or more days following adoption. We are particularly interested in the periods (i) 6 to 14 days following adoption and (ii) two or more weeks following adoption, as these represent the periods following the median and 99th percentile thresholds, respectively, in the incubation window for COVID-19 (Lauer et al. 2020).[19]

With regard to control variables, $PARTORDER_{st}$ is an indicator for whether at least 50 percent of the state population were covered by a local SIPO, $LIMITORDER_{st}$ is an indicator for whether a non-essential business closure was adopted, or a state enacted statewide SIPO for elderly individuals or those with underlying health conditions, $TRAVEL_{st}$ is an indicator for whether a state required visitors or residents to self-quarantine for 14-days upon visiting or returning to the state, $EMERG_{st}$ is an indicator for whether the Federal government had declared the state a major disaster area due to the coronavirus crisis, $TEMP_{st}$ denotes the average high

[19] The period from 1-14 days is the 99 percent confidence interval for the incubation period for coronavirus (Lauer et al. 2020).

temperature in the state, and $PRECIP_{st}$ is an indicator for whether measurable precipitation had fallen in the state.[20]

In addition, α_s is a set of state fixed effects to control for fixed differences across states in COVID-19 infections due to, for example, baseline hospital capacity differences, population density, the presence of an important airport hub, or baseline testing capacity; γ_t is a set of day fixed effects to control for national factors that commonly affect state COVID-19 infections such as national travel restrictions, announcement of Federal guidelines, expansion of COVID-19 testing capacity, general awareness and proliferation of concern regarding COVID-19, or important news pronouncements by National Institutes of Health Infectious Diseases Head Anthony Fauci. Finally, we include controls, α_s*t, for state-specific linear time trends to capture any unmeasured state-level time trends that could be coincidentally associated with the timing of a state coronavirus outbreak and SIPO adoption. Importantly, the state trends help to account for unobserved factors driving the exponential growth trajectory of transmissions, and our effects would be identified off deviations from this trend growth. In alternate specification checks, we also include controls for census region- or census division-specific day effects to account for common unmeasured spatial shocks.

Identification of our key coefficients of interest, β_1 to β_4, comes from within-state variation in SIPO adoption. Over the period under study, 40 states and the District of Columbia adopted SIPOs (see Table 1). It is important to note that our estimates of β_1 to β_3 capture the impact of the SIPO itself over and above any impacts from general increases in social distancing and avoidance behaviors common to treated and untreated states.

[20] Data for emergency decrees for major disaster areas are available at the US Department of Homeland Security - Federal Emergency Management Agency, found here: https://www.fema.gov/disasters. Daily data on temperature and precipitation are available at: https://www.ncdc.noaa.gov

To address the possibility that endogenous COVID-19 testing may conflate the effects of SIPOs on COVID-19 cases, we measure data on testing from the COVID Tracking Project, compiled by *The Atlantic* and *Related Sciences* from state public health authorities.[21] The variable $TESTS_{st}$ measures the cumulative number of COVID-19 tests conducted in state *s* on day *t*. We explore (i) whether SIPOs are associated with changes in log testing rates, and (ii) how the estimated coefficient β_1 changes when we control for state-specific changes in testing. Endogenous adoption of SIPOs is an important concern. For instance, some jurisdictions may adopt SIPOs in response to a noticeably accelerating COVID-19 outbreak (Gupta et al. 2020). To explore the degree to which policy endogeneity is a concern, out primary strategy is to conduct an event-study analysis. That is, we plot the daily coefficients of interest from 7 days prior to enactment through 15 or more days following its enactment. This will allow us to examine whether pre-treatment COVID-19 case trends were common across jurisdictions. We also conduct separate analyses to address heterogeneity in the effects across early adopting states, which instituted a SIPO relatively early in the national outbreak, vs. later adopters.

Finally, to explore the association between statewide SIPOs and COVID-19-related deaths, we turn to a negative binomial model. As can be gleaned from Appendix Table 2, approximately 27 percent of state-days in our sample had a death count of zero. Thus, we estimate a negative binomial model of the following form:

$$\begin{aligned} COVIDDEATH_{st} = \exp(&\beta_0 + \beta_1 * SIPO\_1to5_{st} + \beta_2 * SIPO\_6to14_{st} + \beta_3 * SIPO\_15to19_{st} + \\ &\beta_4 * SIPO\_20plus_{st} + \beta_5 * LIMITORDER_{st} + \beta_6 * PARTORDER_{st} + \\ &\beta_7 * TRAVEL_{st} + \beta_8 * EMERG_{st} + \beta_9 * TEMP_{st} + \beta_{10} * PRECIP_{st} + \alpha_s + \gamma_t + \\ &\alpha_s * t + \varepsilon_{st}) \qquad (2) \end{aligned}$$

[21] These data are available at: https://covidtracking.com

where COVIDDEATH_{st} is the count of COVID-19 related deaths in state *s* on day *t*. We include the same controls as model (1) and use state-level population as an exposure measure. In addition, we also utilize a Tobit regression model and Poisson regression model and find results that are qualitatively similar.[22]

All regressions described above are weighted using the state population and standard errors are corrected for clustering at the state-level (Bertrand et al., 2004).

4. Results

4.1 Statewide SIPO and Social Distancing

We begin by examining the effect of statewide SIPOs on social distancing. Table 2 presents estimates of the relationship between state SIPOs and the percent of individuals who stayed at home throughout the day. In our most parsimonious specification, which includes state fixed effects, day fixed effects and a control for pre-treatment SIPO-state specific linear time trend (to control for differential voluntary social distancing in the pre-treatment period), we find that the enactment of a SIPO is associated with a 1.2 percentage-point increase in stay-at-home rates. This marginal effect represents a 5.2 percent increase relative to the mean pre-treatment stay-at-home rate among future SIPO-adopting states.

Event study analysis shown in Figure 4 suggests an interesting pattern of results. Differential pre-treatment trends are relatively flat, and there was a sharp and steep relative increase in stay-at-home rates in treatment versus control states in the week following the

[22] These findings are available upon request.

policy's adoption. We interpret these findings as evidence that the SIPO had an important short-run impact on social distancing.

However, following the first week after SIPO enactment, the stay-at-home differential between treatment and control states experienced a slight decline before leveling off. This result can be interpreted in several ways. First, the finding could suggest that residents become complacent over time and reverted back to usual habits. Such an effect could have been exacerbated by "cabin fever," a belief that a week was sufficient time for a SIPO to have worked, or diminishing marginal utility (or perhaps disutility) of family time such that facing the expected risk of coronavirus is rationally preferred to staying at home. However, trends in the percent of individuals sheltering-at-home are positive throughout the sample period for the SIPO adopting states, and do not indicate an absolute decline in such social distancing behaviors. Second, a SIPO might have led to short-run panic, including an overestimation of the risk of serious COVID-19 illness. Additional time to overcome the negative emotional shock of being ordered to shelter in place, along with gathering of more health information, may have led to a more accurate assessment of risk of contracting serious illness from venturing outside of one's home. Third, those who were sheltering in place full-time may have learned appropriate precautions to take to increase safety while venturing away from their residences.

Of course, the explanation could also reflect factors other than behavioral responses by residents of SIPO-adopting states. For instance, a lagged increase in voluntary social distancing by those in control states, perhaps in response to widespread SIPO adoption in other states or general proliferation of awareness and concern regarding COVID-19, may have led to greater convergence in rates of staying at home.[23] It is important to note, however, that even if SIPOs merely accelerated sheltering in place in treated versus untreated states, and both sets of states achieved the same level of social distancing eventually, there may be meaningful benefits to SIPO-adoption in the longer term by slowing spread of the illness earlier in the outbreak cycle.

Next, we test the sensitivity of our estimates to controls for state-specific linear time trends across treatment and control states through the entire sample period (columns 2). In this specification, the estimated marginal effect is larger, suggesting that SIPO adoption is associated with a 2.1 percentage-point increase in the share of the population staying at home time, representing a 9.3 percent increase relative to the mean. When we include controls for other COVID-19 orders (column 3), travel restrictions, disaster declaration (column 4), and weather controls (column 5), the results do not change. We find consistent evidence of a 2.1 to 2.3 percentage-point increase in stay-at-home rates, representing daily increases in social distancing of about 9.3 to 9.9 percent relative to the mean stay-at-home rate. These findings are largely consistent with those of Friedson et al. (2020), Gupta et al. (2020), and Abouk and Heydari (2020).

Together, our findings thus far suggest that SIPOs were effective, particularly in the short term, in encouraging residents to stay at home. But are our difference-in-differences findings simply a replication of Friedson et al.'s (2020) results on the stay-at-home effects of California's SIPO? In column (6), we drop California from our analysis sample. While the magnitude of the estimated SIPO effect declines to 2.0, it remains statistically distinguishable from zero at

[23] Or, the effects could reflect sample composition effects, as only 29 of 41 SIPO-adopting states identify the coefficient for the post-14 day lagged effect. However, restricting the sample of states to those 29 states reflected a qualitatively similar pattern of results (see Appendix Figure 1).

conventional levels. Moreover, we cannot reject the null hypothesis that the coefficients reported in columns (5) and (6) are statistically equivalent.

Finally, in column (7), we drop New York and New Jersey from the analysis sample. These states are outliers with respect to both COVID-19 case levels and annual growth rates, owed to outbreaks in the high-population density cities of New York City and Jersey City. From March 8 through April 20, the average daily increase in COVID-19 cases per 100,000 population was around 8 times higher in New York and New Jersey as compared to the remaining 49 (26.9 daily cases per 100,000 population vs. 3.4 daily cases per 100,000 population). In addition, these states were also early adopters of SIPOs, perhaps in response to the gathering storm of outbreak. When we drop these states from our sample, the estimated effect of SIPO adoption on stay-at-home rates are unchanged.

4.2 Statewide SIPOs and COVID-19 Cases

We begin our coronavirus case analysis with a sample including 48 states and the District of Columbia, excluding the two states on a very different case growth trajectory, New York and New Jersey. However, we will return to these states shortly.

In Table 3, we present difference-in-differences estimates of the effect of SIPO adoption on COVID-19 cases.[24] In our most parsimonious specification, we find little evidence that COVID-19 cases were affected during the 5 days following a SIPO's enactment. This is not too surprising given that transmission may not be as common during an asymptomatic incubation period.[25] However, the estimated coefficients on the SIPO policy become much larger after 6 to

[24] Appendix Table 3 presents coefficients on the control variables for the regressions shown in Table 3.
[25] This finding could also be explained by lags in COVID-19 testing.

14 days. After 20 days of adoption, enactment of a SIPO is associated with a 37.7 percent decline in COVID-19 cases (column 1), though this effect is imprecisely estimated.[26]

In column (2), we add controls for state-specific linear time trends as additional controls. We believe this specification is preferable to that shown in column (1) for two reasons. First, in a model with log cases as the outcome, state linear trends control for the state-specific exponential growth path of the outbreak (at least prior to reaching the peak number of cases), making the estimated effect of the SIPO deviations from that growth path. Second, with regard to the common trends assumption, the specification including state-specific linear time trends is more defensible when examining event studies, as the pre-treatment trends are flatter.[27]

In column (2), we find that between 6- and 14-days following enactment of a SIPO, there was a 28.0 percent decline in COVID-19 cases, an effect that is statistically distinguishable from zero at the 10 percent level. In this instance, the inclusion of state-specific linear time trends generates a more precisely estimated coefficient as it soaks up some of the residual variance. Moreover, 15 to 19 days after SIPO adoption, we find that coronavirus cases fell by 37.8 percent. And after 20 days after SIPO adoption, we find that coronavirus cases fell by 45.1 percent, suggesting that the health benefits of SIPOs may grow larger in the periods following enactment.

The remaining columns of Table 3 show the robustness of the COVID-19 case results to observable state-level observable controls. We find no evidence that other COVID-19-related shutdown or shelter policies (column 3), travel restrictions or major disaster emergency declarations (column 4), or weather (column 5) affected the estimated impact of SIPOs on

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[26] This estimate is calculated as $(e^{-0.473}-1)*100=37.7$

[27] COVID-19 case specifications that include state-specific linear time trends (see Figure 5, Appendix Figure 3) produce much stronger evidence of common pre-treatment trends than the two-way fixed effects model (Appendix Figure 2).

COVID-19 cases.[28] In our preferred specification (column 5), we find that between 6 to 14 days following a SIPO, coronavirus cases fell by 25.5 percent, between 15 to 19 days following a SIPO, coronavirus cases fell by 35.6, and approximately three weeks following adoption, coronavirus cases fell by 43.7 percent.[29]

An event-study analysis of COVID-19 cases from the specification described in column (5) is shown in Figure 5. We find very little evidence of differential pre-SIPO COVID-19 case trends in treatment and control states during the week prior to adoption. Each of the leads is statistically indistinguishable from zero and each point estimate is near zero. Following the adoption of the policy, estimated case reductions accelerate over time, becoming largest after 20 days following enactment of a SIPO. These findings are consistent with a causal interpretation of our findings from Table 3 and with exponential growth in short-run health benefits during the period of the shelter-in-place order.[30]

4.3 Sensitivity Analysis

In Table 4, we explore the sensitivity of our main findings to the inclusion and exclusion of states from the analysis sample. Above, we argued for the exclusion of New York and New Jersey from our sample. In column (1) of Table 4, we include these states in the analysis sample.

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[28] In Appendix Table 4, we explore the lagged effects of non-essential business closure policies, which was a common policy adopted just prior to full SIPOs or instead of SIPOs. We find no evidence that non-essential business closure policies affect the number of COVID-19 cases.
[29] In alternate specifications, available upon request, we estimate negative binomial and tobit regressions of the effect of SIPOs on COVID-19 cases. The findings are qualitatively unchanged from those we report.
[30] We test the sensitivity of our estimated policy impacts to including an additional week of pre-treatment COVID-19 case data. The pattern is largely unchanged. Moreover, when we allow each post-treatment day to have its own estimated SIPO effect, we continue to see a similar pattern of findings, albeit less precisely estimated (Appendix Figure 3).

The estimated effect of SIPO adoption on coronavirus cases is quite similar to that reported in column (5) of Table 3 (-.485 vs -.575).[31]

Given that California's SIPO is significantly associated with a decline in coronavirus cases (Friedson et al. 2020), we next excluded this state from the analysis to ensure that our findings were not driven by the earliest-adopting state for which there is already strong evidence for SIPO-induced COVID-19 case reductions. Our results show that the average SIPO effect we detect is not driven by California. Excluding California, we find that 20 days following SIPO implementation, COVID-19 cases fell by 35.1 percent. Event-study analysis based on this sample, provided in Figure 6, shows no evidence of pre-treatment trends in the week following SIPO adoption and a similar pattern of case declines that grow larger in the weeks following enactment.

In columns (3) through (7), we exclude a number of states with high COVID-19 case levels (relative to the national mean), as well as states with relatively high COVID-19 case rates. The states we drop include Washington (column 3), Massachusetts (column 4), Louisiana (column 5), District of Columbia (column 6), and Connecticut (column 7). The results show that the average SIPO effect we detect is not also driven by these states. We estimate that, after 20 days of enactment, SIPO adoption is associated with a 40.2 to 45.6 percent reduction in COVID-19 cases when we exclude these states from our sample.

[31] Appendix Figure 4 shows an event-study analysis when we include New York and New Jersey in the main analysis sample. Note that as we approach the period over one week prior to adoption, the coefficient estimates decrease, suggesting a pre-treatment upward trend in cases when we include New York and New Jersey to our sample.

In the final three columns of Table 3, we drop several states with lower rates of coronavirus and low rates of coronavirus case growth: Oregon (column 8), Texas (column 9), and Minnesota (column 10). Again, we find no evidence that our main finding is changed.

One concern with the estimates presented thus far is that they may be biased if SIPO adoption were correlated with COVID-19 testing capabilities. This may be the case due to the evolution of testing over the period of analysis. As of March 13, only 15,000 tests had been conducted in the U.S. To address the low testing rate in the U.S., the Food and Drug Administration approved a new COVID-19 test from the pharmaceutical company Roche (Arnold 2020). In the following days, Delaware, New York, Massachusetts and Texas, began implementing drive-up testing sites, which made testing more accessible (Yancey-Bragg 2020). Despite these improvements in accessibility, many testing delays persisted due to laboratory capacity constraints (Brown and Court 2020).

SIPOs could affect COVID-19 testing in several ways. First, SIPOs may induce some who have flu-like symptoms to stay at home rather than seek medical attention, either due to perceived civic duty or a perception of greater adverse selection in patients who present at medical facilities during a pandemic. Second, SIPOs could strain public resources such that there is a budgetary tradeoff in enforcing SIPOs and expanding COVID-19 testing capabilities. On the other hand, if SIPOs are effective at reducing caseloads, medical resources that no longer have to be used to treat coronavirus patients can be used to expand testing. Moreover, if SIPOs prevent symptomatic COVID-19 cases, fewer patients will present for testing.

Data on COVID-19 testing are obtained from COVID Tracking Project.[32] A test is counted if the result was deemed positive, negative, or inconclusive. In Appendix Table 1, we

[32] See https://covidtracking.com. Note that COVID-19 testing data are missing for *some* days for the following states: Alabama, Delaware, Kansas, Maryland, Michigan, and Ohio.

report that the average testing rate over the sample period was 363.8 tests per 100,000 population.

The first two columns of Table 5 show estimates of the effect of SIPOs on the natural log of COVID-19 tests. We find that SIPOs are negatively related to testing, but these effects are never statistically distinguishable from zero at conventional levels. In light of these findings, it is perhaps not surprising that in columns (3) and (4) of Table 5, we find no evidence that the estimated effect of enactment of a SIPO on COVID-19 cases is affected by the addition of a control for COVID-19 testing capacity. Given that testing is a potentially endogenous control (though we do not find any evidence that it is affected by a SIPO), we nevertheless take this descriptive evidence as suggestive of the hypothesis that our estimates are not biased due to state-level heterogeneity in growth of testing capacity.

The difference-in-differences estimates presented to this point have identified the effect of a SIPO on the state-specific change in cumulative cases of coronavirus. In Table 6, we explore the effect of SIPO adoption on the "derivative" of cumulative COVID-19 cases, that is, daily COVID-19 cases. And, in fact, we find evidence that the enactment of a SIPO also affected the rate of change in cumulative COVID-19 cases. The results suggest that state adoption of a SIPO was associated with a 44.6 to 47.5 percent decline in daily coronavirus cases.

In Table 7, we explore the sensitivity of our cumulative (columns 1 and 2) and daily (columns 3 and 4) case regressions to controls for common regional time shocks. The results are quite robust to the inclusion of these controls, with estimated case effects for the post-19 day SIPO window suggesting a decline of 35.4 to 40.9 percent.

4.4 Statewide SIPO and COVID-19 Mortality

Next, we turn to an analysis of whether statewide SIPOs affected mortality. There are several channels through which mortality may be affected by SIPOs. If SIPOs reduce coronavirus cases, mortality will decline in the longer-run because fewer people will become infected with the coronavirus. Of course, these effects are likely to come with a much longer lag than cases given that the time from first symptoms until acute respiratory distress syndrome (ARDS) is, on average, about 8 days (Wang et al. 2020). In addition, SIPOs may affect the likelihood that infected patients choose to stay at home rather than seek out testing and other medical care, having the unintended consequence of increasing serious illness and death. Finally, SIPOs may also impact the availability of resources for medical care, as public resources are used to enforce SIPOs instead.

Negative binomial regressions of the effect of SIPO enactment on COVID-19-related mortality are shown in Table 8. We find that the results are sensitive to our specification model. In a model without state-specific linear time trends (columns 1 and 2), we find that the mortality effect becomes stronger. Columns (1) to (2) suggest that after 20 days, SIPO adoption is associated with 47.1 to 53.7 percent reduction in mortality. Controlling for state-specific linear time trends, the estimated mortality effects are somewhat smaller, but continue to show long-run COVID-19 death declines. But because none of these estimates are statistically distinguishable from zero at conventional levels, we can only cautiously interpret these findings as evidence of mortality declines. We note here that due to the longer lag with which we expect mortality effects to materialize, the effects for the longer time windows (15-19 days post SIPO, > 19 days post SIPO) are identified off a few early-adopting states. Hence, more long-run data is necessary for a definitive conclusion.

In Figure 7, we show the event study analysis on COVID-19 related mortality, obtained from the negative binomial regression shown in column 4 of Table 8. We find no evidence of differential pre-treatment trends in mortality, with a longer delayed potential decline in mortality.

4.5 Heterogeneity in Estimated Impacts of SIPOs

The results presented above provide consistent evidence that the adoption of a statewide shelter-in-place order significantly reduced infection rates, with the strongest effects realized two or more weeks after enactment. This lag is consistent with the incubation period of the virus (2-14 days) over which transmission may be possible but less efficient due to lack of symptoms. Given the exponential growth trajectory of infection, there may additional dynamics in terms of the effectiveness of the SIPO depending on when the policy is enacted – whether early or late over the cycle of disease progression. That is, the beneficial effects of social distancing on COVID-19 caseload may have an accelerating effect over time if enacted early.

Friedson et al. (2020) find strong evidence that California's first-in-the-nation SIPO had a strong public health benefit, and continued to do so even after social distancing measures between California and its control narrowed. This is suggestive of persistent and magnified effects of enacting a SIPO early in the outbreak cycle. However, given the study's focus on California, Friedson et al. (2020) were not able to explicitly test for heterogeneity in the response across early vs. late adopters. Table 9A presents effects separately across early adopting states (adopted on March 25 or earlier) and late adopting states (adopted after March 25). These results confirm that the effects are primarily driven by states which enacted the shelter-in-place orders relatively early, thus capitalizing on the magnified benefits of social distancing as the growth trajectory was rising but still relatively low compared with later adopters. In addition, we now uncover some evidence that SIPOs are effective at reducing coronavirus-related mortality when they were adopted early in the COVID-19 outbreak epidemic in the U.S. While some of this result could be explained by insufficient longer-run data from later adopters, all later adopters and early adopters have data between 2 and 3 weeks after SIPO adoption and early adopters see substantially larger health benefits than earlier adopters over this period.

In Table 9B, we explore whether COVID-19-related health benefits are larger among states with higher population density. To do this, we explore the interquartile range of population density rankings of U.S. states.[33] In the main, our findings suggest larger COVID-19-related health benefits among those outside the lower 25th percentile of state population density rankings. Those states in the middle 50th percentile and upper 25th percentile of population density tend to see larger reductions in COVID-19-related cases. This result is consistent with the hypothesis that stay-at-home orders are likely to generate greater health benefits when crowd-related contagion is avoided. The relationship between population density and the marginal effect of SIPOs on mortality appears more non-monotonic.

Together, the findings in Tables 9A and 9B generally suggest compounding and stronger effects of social distancing among the early adopters and higher population density states and provide some explanation as to why the SIPOs continue to have a beneficial effect on infection rates 6 to 20+ days post-enactment.[34] In Table 9C, we test this hypothesis by presenting estimates of the effect of SIPOs on stay-at-home rates by (i) whether the enacting state was an early or later adopter, and (ii) the interquartile range of population density.

[33] We obtain our population density measures here: https://www.statista.com/statistics/183588/population-density-in-the-federal-states-of-the-us/

[34] Event-study analyses on early-adopting and more densely populated states, available upon request, produces a pattern consistent with coronavirus case differentials that trend near zero in the pre-treatment period and fall precipitously following SIPO enactment.

First, consistent with our health results our findings in Panel I provide strong evidence that SIPOs were more effective at increasing social distancing in early adopting as compared to later adopting SIPO states. The estimated social distancing effect was twice as large for early as compared to later-adopting states (2.6 percentage-points vs 1.3 percentage-points). One explanation for our finding may be that residents of later-adopting SIPO states already adopted some social distancing behaviors prior to their SIPO adoption or because later-adopting SIPO state residents were less compliant with social distancing mandates, perhaps because of political or ideological preferences (Painter and Qiu 2020).

Next, if the primary mechanism through which SIPOs impact case rates is through social distancing, then we would expect these benefits to be further magnified in states with a high population density. Population density is an independent predictor of community spread of infection; SIPOs therefore would have more capacity to reduce social distancing in these states, and a given decrease in social distancing would also translate into reduced modes of person-to-person contact. In Panel II Table 9C, we assess heterogeneity in the effects on stay-at-home behaviors across states with lower versus higher rates of population density, as measured by population per state area in square miles. Consistent with our findings on COVID-19, we find that SIPOs are more effective in promoting social distancing in more densely populated states. The patterns uncovered in Table 9C, with respect to heterogeneity in social distancing, parallel the stronger health effects that we find among states that adopted the orders earlier and among more densely populated states.

Finally, our research design, based on a difference-in-differences estimator, capitalizes on the treatment turning on at different times and thus on the differential timing of SIPO adoption across states and over time. Goodman-Bacon (2018) shows that the treatment effect in this case is a weighted average of all possible two-group and two-period DD estimators.[35] In other words, our main treatment effect is identified off many "mini" experiments comparing: 1) early- and late-adopting states with never-adopting states as controls; 2) early-adopting states with late-adopting states as controls; and 3) late-adopting states with early-adopting states as controls. We apply the decomposition method outlined in Goodman-Bacon (2018) in order to gauge heterogeneity in our estimated treatment effects across each of these margins and control groups (see Figure 8).[36] This exercise provides important information in two respects. First, it makes transparent which sets of these comparisons are driving identification. Second, because of the compounding and multiplicative effects of SIPOs that are adopted early, using early-adopting states as controls for late-adopting states when they enact their own SIPOs may not provide a valid counterfactual. This is because the trajectory of the early-adopting states, at the time when the late-adopting states enact their own SIPOs, is still being affected by the policy (that is, by the SIPOs in the early-adopting states).

Our decomposition indicates that 71.1 percent of our identifying variation in the post-three-week period comes from comparing adopting states to never-adopters while 26.5 percent of our identifying variation comes from comparing early adopters, when they adopt their SIPOs, to later adopters as controls (when they have not yet adopted their SIPOs). In both of these cases, our estimated treatment effects are negative and comparably sized, which is validating given that two different sets of controls are yielding similar estimates.

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[35]The weights are based on the subsample shares making up each "mini" experiment and the variance of the subsample difference-in-differences estimator relative to the full-sample difference-in-differences estimator. Our focus is on the post-20 day period for the decomposition.

[36] Figure 8 presents the distribution of the treatment effect derived from each mini 2x2 difference-in-differences experiment, across these three margins, in conjunction with the weights associated with each estimated effect. As shown here, the majority of cumulative weight (71.1 percent) is attached to treatment effects estimated from comparing the treated states to those that are never treated.

Finally, the experiment provided by comparing the SIPOs of late-adopters to early adopters (using the early adopters as controls) contributes only 2.4 percent to our identifying variation. Furthermore, the treatment effect for this comparison is close to zero, as expected. Because the controls in this experiment (early adopters) are also treated, one would expect any treatment effects based on this contaminated set of controls to yield smaller and understated estimates.

In summary, virtually all of our identification is coming from comparing states that adopt to states that have never adopted or by comparing early-adopting states with states that had not yet adopted the shelter-in-place order, but did so later. Both of these margins yield treatment effects are highly similar.

5. Conclusions

Since March 19, 2020, 40 states and the District of Columbia have adopted shelter-in-place orders to attempt to hasten the spread of COVID-19, smooth illnesses and treatment over time, and prevent short-run medical capacity constraints from causing otherwise avoidable deaths. Critics, however, argue that SIPOs impose large, and perhaps long-lasting, job loss, strain social insurance programs beyond their capacity, and slow the progression toward community-level herd immunity. While the lack of long-run data does not yet permit us to answer all of the claims made by proponents and opponents of SIPOs, this paper proposes an important first step: to estimate the short-term impact of statewide SIPOs on COVID-19 cases and COVID-19-related mortality. That is, did these policies meet their immediate public health objective?

First, using GPS-based anonymized cell phone records from SafeGraph, Inc. to measure state-level daily social mobility, we find evidence that the enactment of a state SIPO resulted in a short-run increase in the percent of state residents remaining at home full time. While longer-run differentials in stay-at home rates for treatment and control states were smaller or slightly negative, the findings do suggest an important effect of SIPOs on social distancing.

Second, using coronavirus case and mortality data from March 8, 2020 to April 20, 2020, and a difference-in-differences approach, we find that approximately three weeks after the enactment of a statewide SIPO, the average number of cumulative cases fell by approximately 44 percent. Approximately 3 to 4 weeks following SIPO adoption, this corresponds to approximately 2,510 fewer cumulative COVID-19 cases for the average SIPO-adopting state. Event study analysis suggests that this result was not driven by differential pre-treatment trends, nor was it driven by the California experience (Friedson et al. 2020). We find that states that were highly urbanized and were early SIPO adopters saw the largest declines in cases, consistent with the hypothesis that early adopters with high population densities had the largest margins for larger short-run public health benefits.

The larger efficacy of a statewide SIPO depends on a number of factors beyond the specific scope of our paper. But if we assume (i) SIPOs are temporary because the economic costs are substantial, (ii) development of a vaccine or effective treatment for COVID-19 is unlikely in the short-run (Fauci 2020), and (iii) universal (or at least widespread) testing of asymptomatic individuals is also very unlikely in the short-run (Center for Disease Control and Prevention 2020d), some of the short-run COVID-19 cases and deaths may simply be postponed to the near future when the SIPO is lifted. In that case, deaths and serious illnesses averted by avoiding short-run shortages of ventilators, hospital beds, and medical professionals may be a SIPO's most likely path to generating long-run public health benefits.

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Figure 1: Total Cases by State and Day

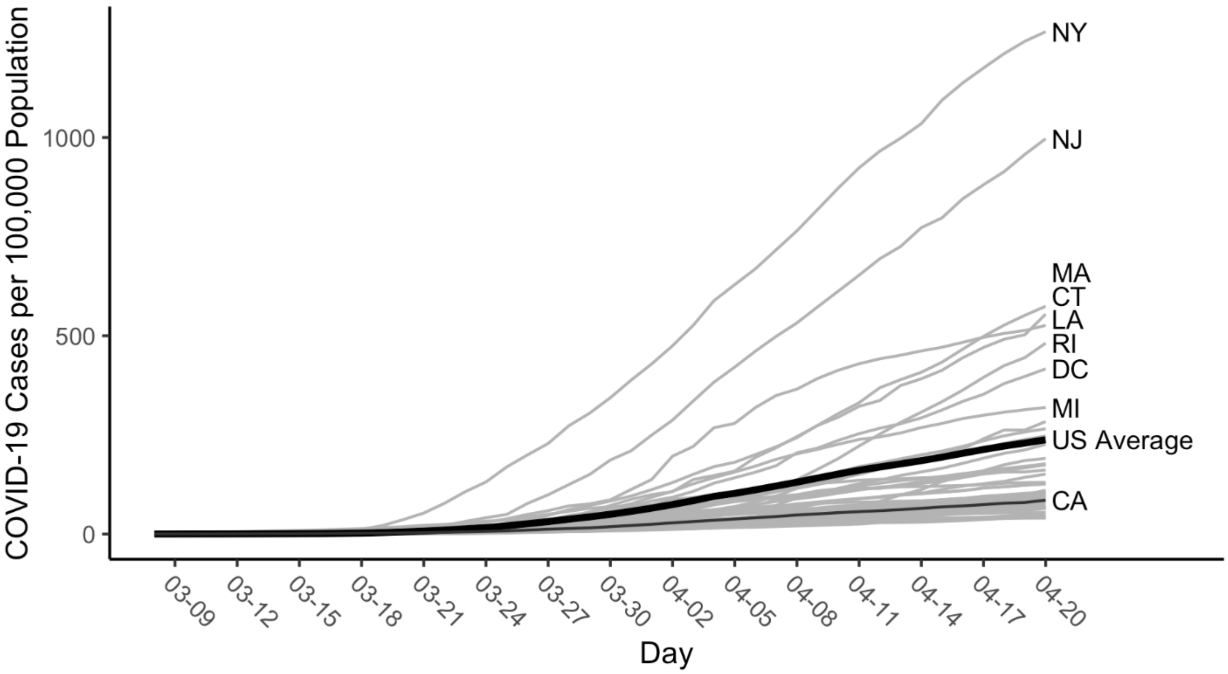


Figure 2: Total Deaths by State and Day

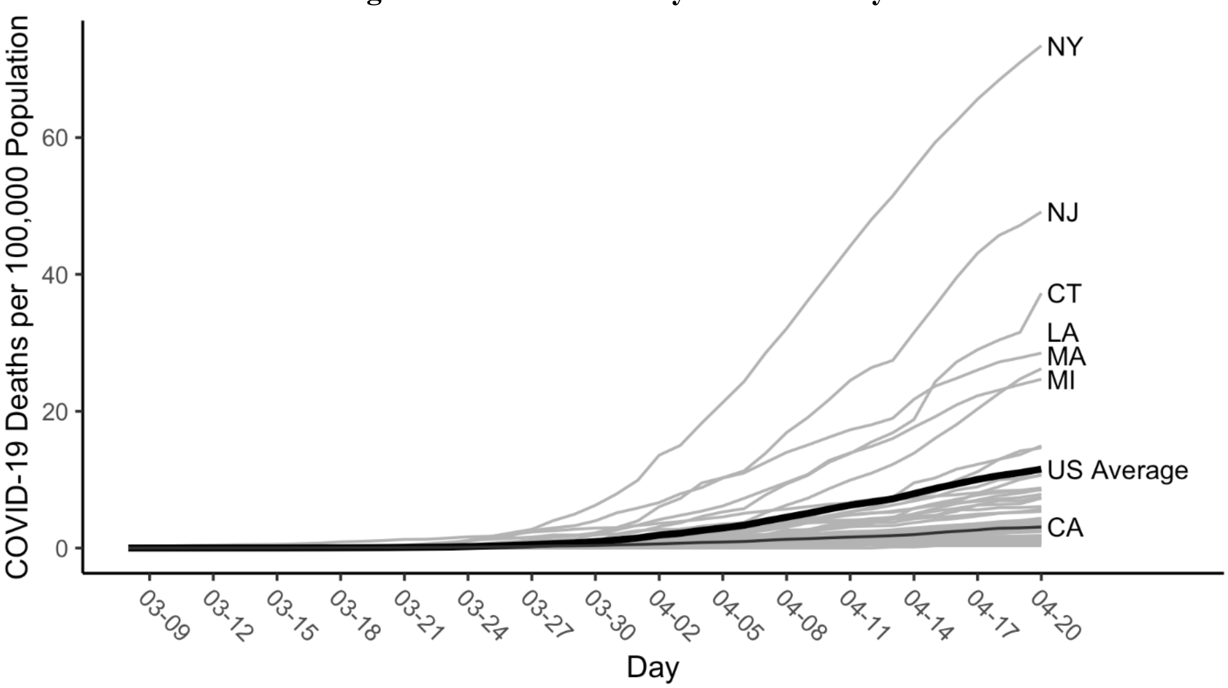


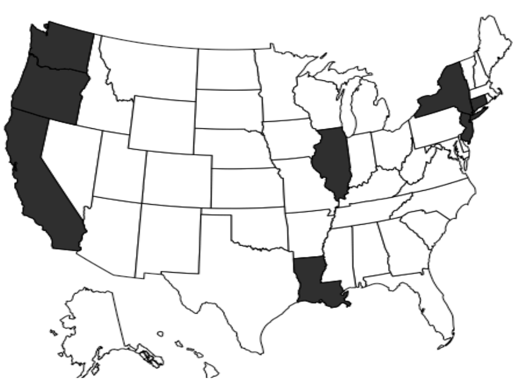
Figure 3: Enactment of Statewide Shelter-in-Place Orders (SIPOs)

March 19

March 21

March 22

March 23



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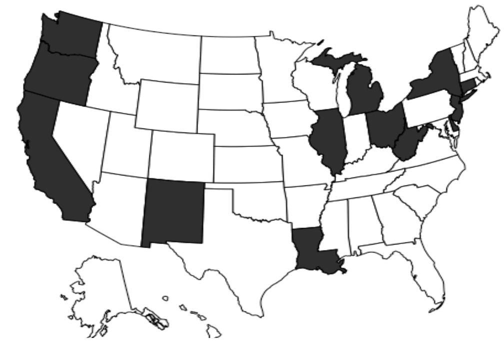
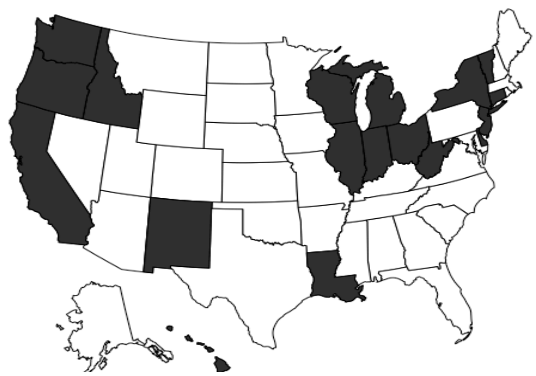


March 25



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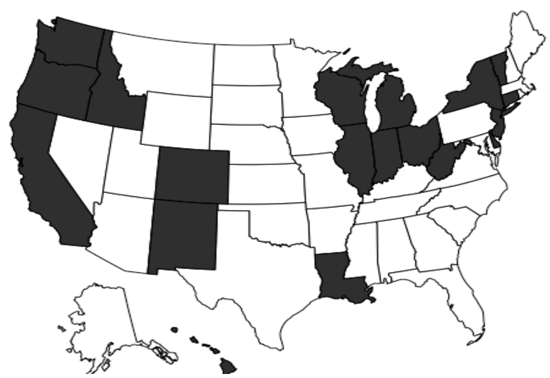


March 28

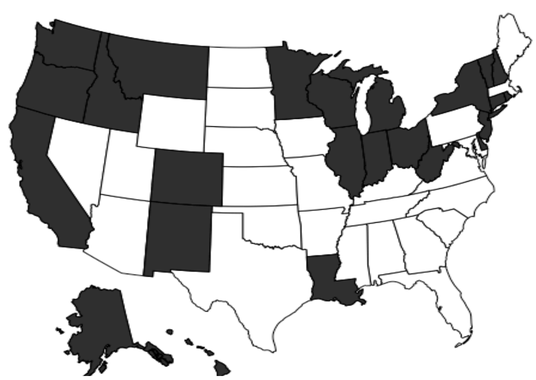
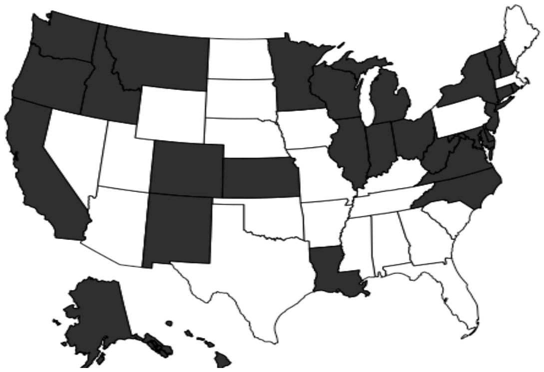
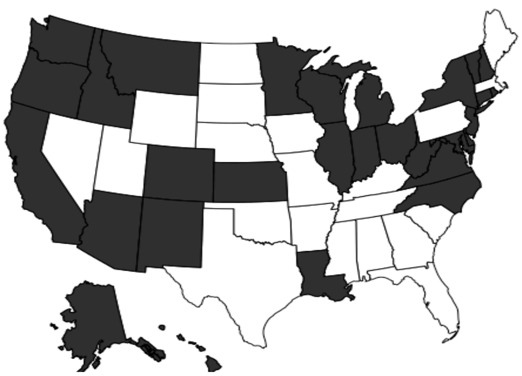


Figure 3: Continued

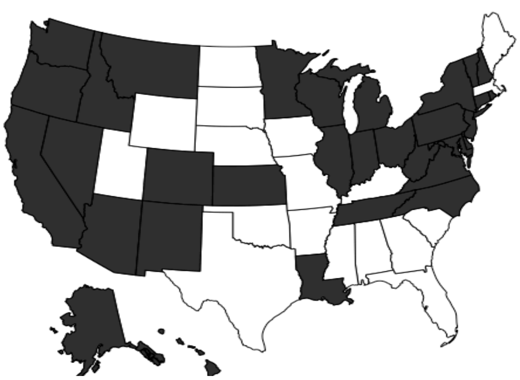
March 30



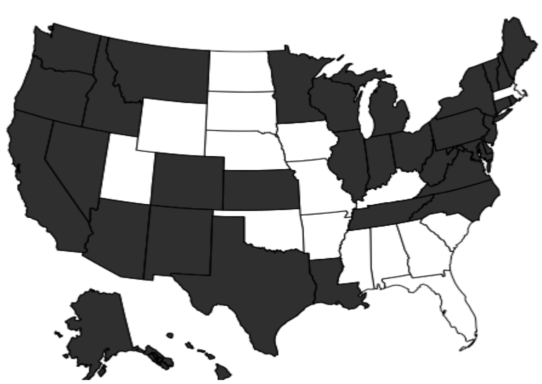
March 31



April 1



April 2



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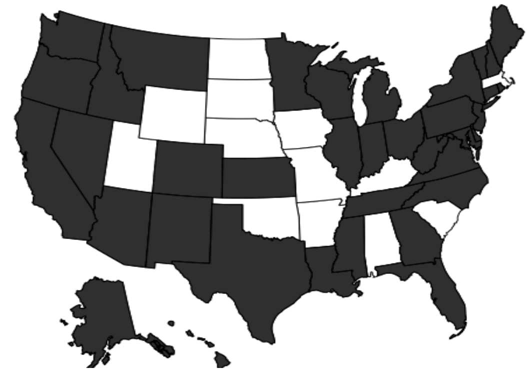

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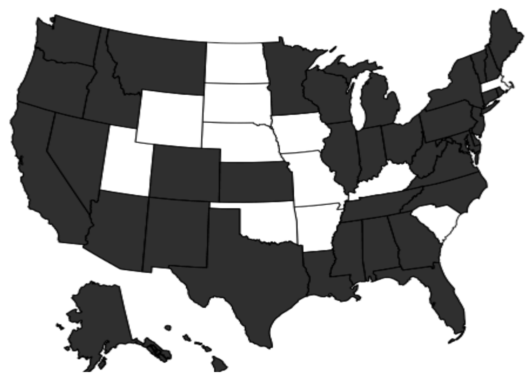
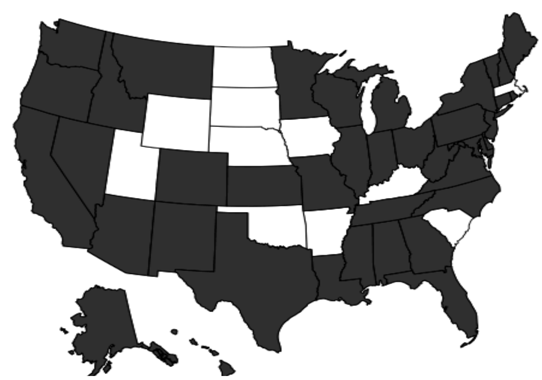


April 6



April 7

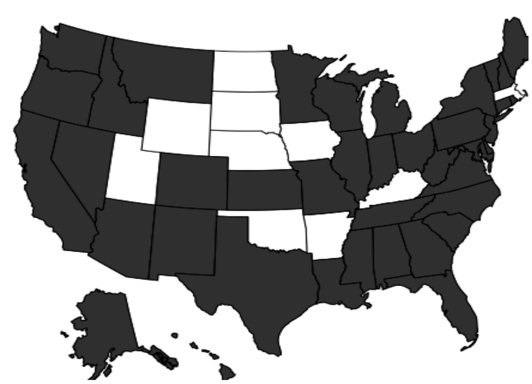
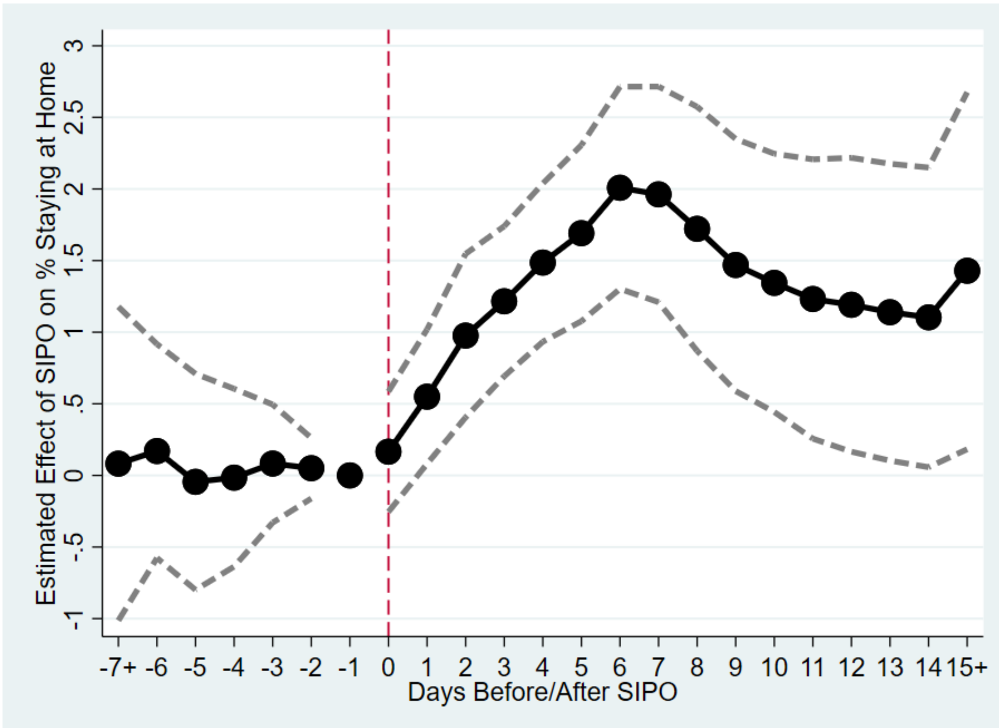
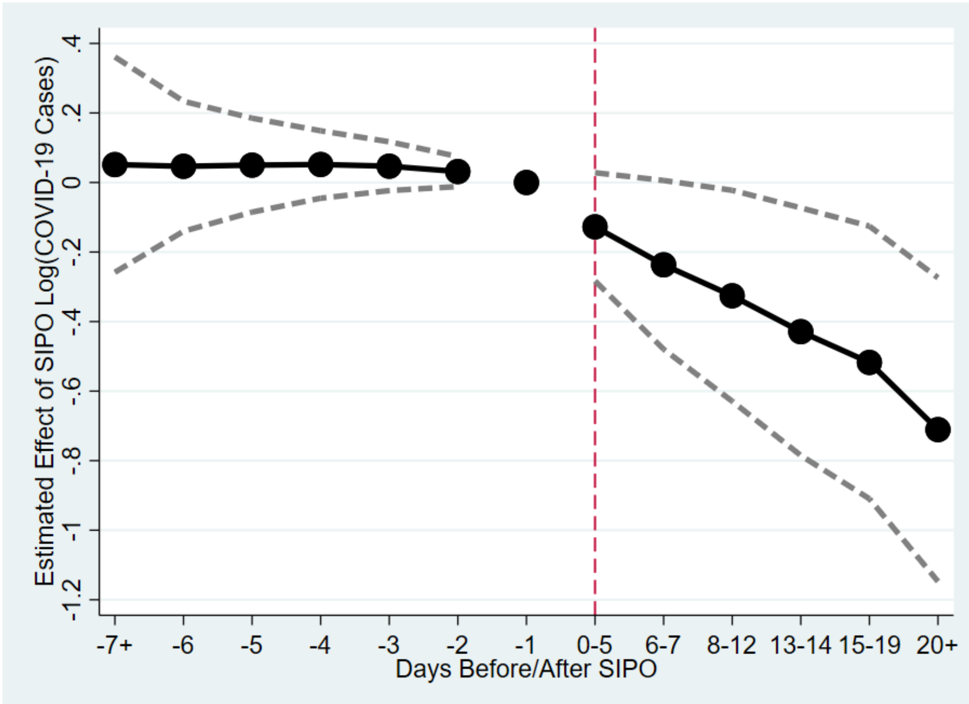


Figure 4: Event-Study Analysis of Shelter in Place Orders (SIPOs) and Percent Staying at Home



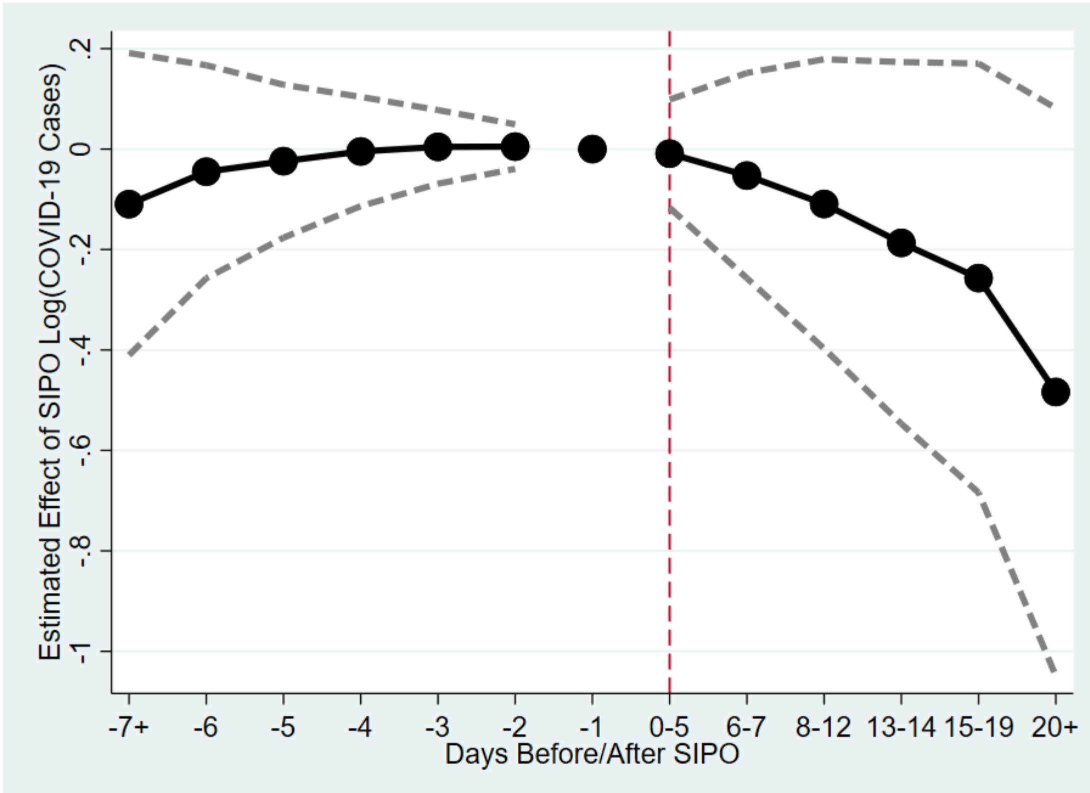
Notes: Estimates are obtained using weighted least squares regression. The model includes controls for state fixed effects, day fixed effects, and state-specific linear pre-trends. Standard errors are clustered at the state level.

Figure 5: Event-Study Analysis of Shelter in Place Orders (SIPOs) and Log (COVID-19 Cases Per 100,000 Population)



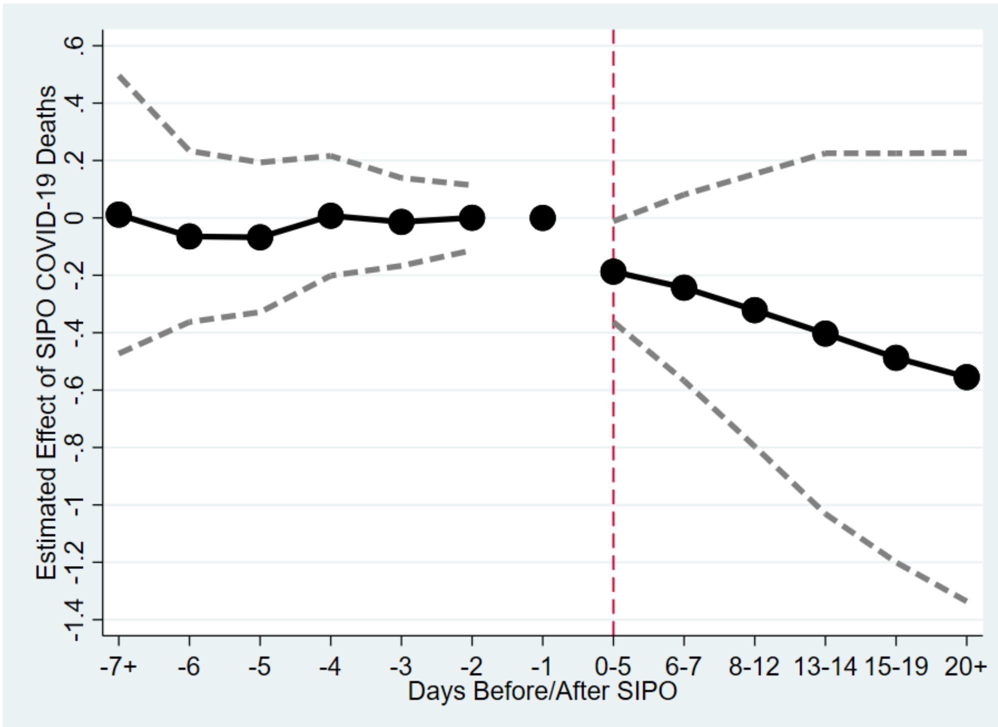
Notes: Estimates are obtained using weighted least squares regression. The model includes controls for state fixed effects, day fixed effects, state-specific linear time trends, and the controls listed in Appendix Table 1. Standard errors are clustered at the state level.

Figure 6: Event-Study Analysis of Shelter in Place Orders (SIPOs) and Log (Daily COVID-19 Cases Per 100,000 Population: Excluding California



Notes: Estimates are obtained using weighted least squares regression. The model includes controls for state fixed effects, day fixed effects, state-specific linear time trends, and the controls listed in Appendix Table 1. Standard errors are clustered at the state level.

Figure 7: Event-Study Analysis of Shelter in Place Orders (SIPOs) and Log (COVID-19 Deaths Per 100,000 Population)



Notes: Estimates are obtained using weighted least squares regression. The model includes controls for state fixed effects, day fixed effects, state-specific linear time trends, and the controls listed in Appendix Table 1. Standard errors are clustered at the state level.

Figure 8: Goodman-Bacon Decomposition of Effect of SIPO on Log (COVID-19 Cases)

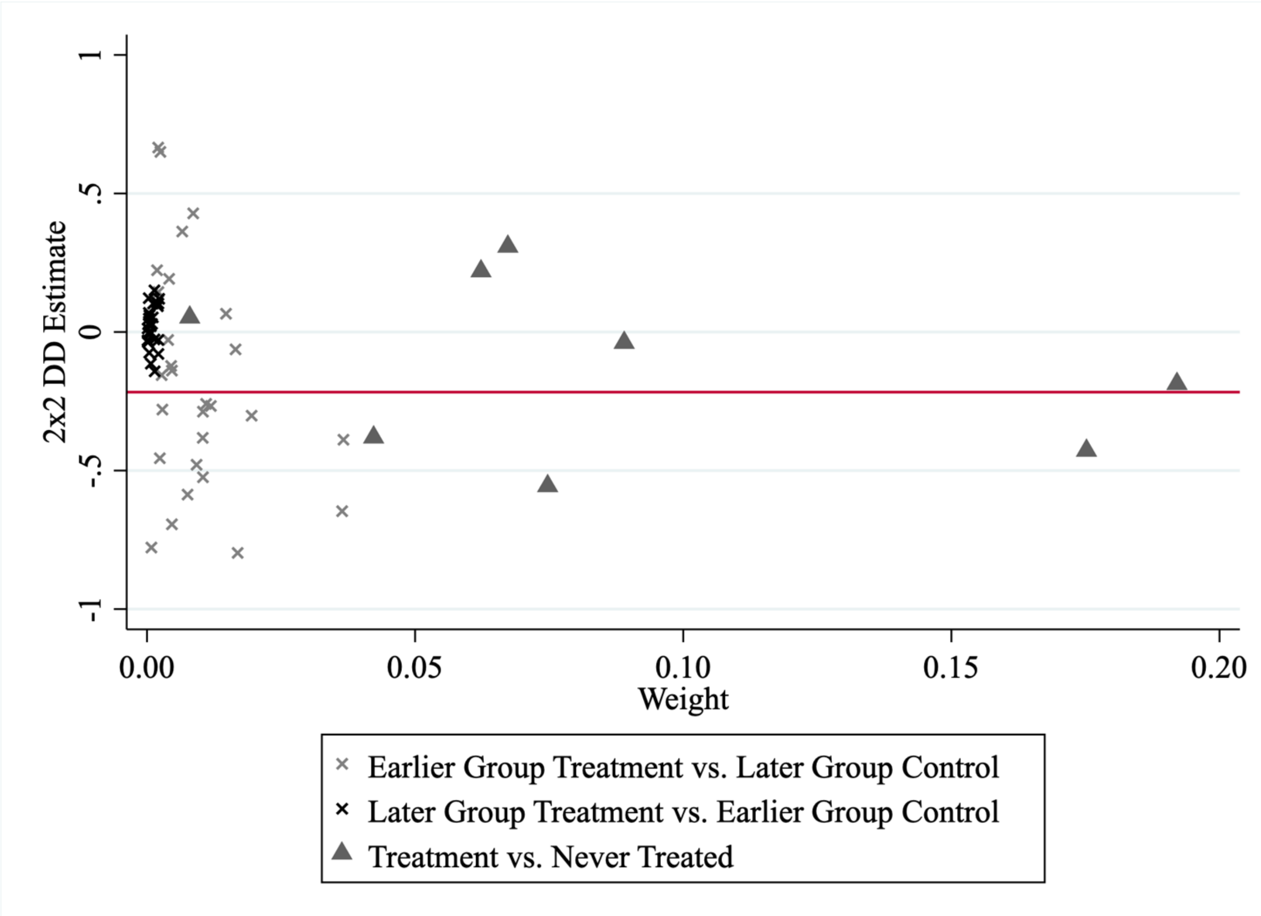


Table 1: Enactment Dates of Statewide SIPOs

State	Date	State	Date
Alabama	April 4	Mississippi	April 3
Alaska	March 28	Missouri	April 6
Arizona	March 31	Montana	March 28
California	March 19	Nevada	April 1
Colorado	March 26	New Hampshire	March 28
Connecticut	March 23	New Jersey	March 21
Delaware	March 24	New Mexico	March 24
District of Columbia	April 1	New York	March 22
Florida	April 3	North Carolina	March 30
Georgia	April 3	Ohio	March 24
Hawaii	March 25	Oregon	March 23
Idaho	March 25	Pennsylvania	April 1
Illinois	March 21	Rhode Island	March 28
Indiana	March 25	South Carolina	April 7
Kansas	March 30	Tennessee	April 1
Louisiana	March 23	Texas	April 2
Maine	April 2	Vermont	March 25
Maryland	March 30	Virginia	March 30
Michigan	March 24	Washington	March 23
Minnesota	March 28	West Virginia	March 24
		Wisconsin	March 25

Source: Mervosh et al. (2020) and the authors' own searches of state executive orders.
Notes: Indiana, Minnesota, New Hampshire, and Ohio implemented a statewide SIPO at 11:59pm on March 24, March 27, March 27, and March 23 respectively. We code each state's SIPO as being effective the minute following its effective time.

In Massachusetts, instead of a formal order, Gov. Charlie Baker issued a "Stay at Home Advisory," which we treated as a non-SIPO.

Table 2. Difference-in-Difference Estimates of the Effect of SIPOs on Percent of State Residents Who Stay at Home

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SIPO	1.181***	2.181***	2.264***	2.200***	2.129***	1.986***	1.995***
	(0.224)	(0.351)	(0.339)	(0.291)	(0.282)	(0.381)	(0.312)
N	2091	2091	2091	2091	2091	2050	2009
State and Day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Specific Linear Time Trend	No	Yes	Yes	Yes	Yes	Yes	Yes
Other COVID-19 Orders	No	No	Yes	Yes	Yes	Yes	Yes
Travel Restrictions and Disaster Declaration	No	No	No	Yes	Yes	Yes	Yes
Weather Controls	No	No	No	No	Yes	Yes	Yes
CA Included?	Yes	Yes	Yes	Yes	Yes	No	Yes
NY & NJ Included?	Yes	Yes	Yes	Yes	Yes	Yes	No

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level.

Notes: Estimates are obtained using weighted least squares regression. The model includes the following controls: an indicator for whether the state had issued a non-essential business closure order (that fell short of a SIPO) or a targeted SIPO for older individuals or those with underlying health conditions, an indicator for whether coverage of local (i.e. city or county) SIPO orders covered at least 50 percent of the state population, an indicator for whether the state had issued restrictions on travel to or from the state, an indicator for whether the state had received a major disaster emergency declaration from the Federal government, the average temperature (in degrees Celsius) in the state, an indicator for whether measurable precipitation fell in the state, state fixed effects, day fixed effects, and a state-specific linear time trend. Standard errors, clustered at the state-level, are reported in parenthesis.
Source for Dependent Variable: SafeGraph 2020. Available at: https://www.safegraph.com/dashboard/covid19-shelter-in-place

Table 3. Difference-in-Difference Estimates of the Effect of SIPOs on Log (COVID-19 Cases)

	(1)	(2)	(3)	(4)	(5)
1-5 Days After SIPO[a]	0.035	-0.146	-0.160	-0.143	-0.137
	(0.114)	(0.116)	(0.126)	(0.109)	(0.103)
6-14 Days After SIPO[a]	-0.086	-0.329*	-0.350*	-0.309*	-0.295**
	(0.235)	(0.170)	(0.180)	(0.157)	(0.141)
15-19 Days After SIPO	-0.214	-0.475**	-0.498**	-0.461**	-0.440***
	(0.331)	(0.193)	(0.203)	(0.184)	(0.162)
20+ Days After SIPO	-0.473	-0.599***	-0.626***	-0.597***	-0.575***
	(0.495)	(0.193)	(0.204)	(0.190)	(0.176)
N	2100	2100	2100	2100	2100
State and Day Fixed Effects	Yes	Yes	Yes	Yes	Yes
State Specific Linear Time Trend	No	Yes	Yes	Yes	Yes
Other COVID-19 Orders	No	No	Yes	Yes	Yes
Travel Restrictions and Disaster Declaration	No	No	No	Yes	Yes
Weather Controls	No	No	No	No	Yes

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level.

Notes: Estimates are obtained using weighted least squares regression. The model includes the following controls: an indicator for whether the state had issued a non-essential business closure order (that fell short of a SIPO) or a targeted SIPO for older individuals or those with underlying health conditions, an indicator for whether coverage of local (i.e. city or county) SIPO orders covered at least 50 percent of the state population, an indicator for whether the state had issued restrictions on travel to or from the state, an indicator for whether the state had received a major disaster emergency declaration from the Federal government, the average temperature (in degrees Celsius) in the state, an indicator for whether measurable precipitation fell in the state, state fixed effects, day fixed effects, and a state-specific linear time trend. Standard errors, clustered at the state-level, are reported in parenthesis.

[a] The 99 percent confidence interval for the incubation period for coronavirus is 1 to 14 days (Lauer et al. 2020).

Table 4. Sensitivity of Findings to the Inclusion or Exclusion of States in Analysis Sample

	(1) *Add NY & NJ*	(2) *Drop CA*	(3) *Drop WA*	(4) *Drop MA*	(5) *Drop LA*
1-5 Days After SIPO[a]	-0.046	0.015	-0.135	-0.135	-0.140
	(0.136)	(0.072)	(0.113)	(0.108)	(0.102)
6-14 Days After SIPO[a]	-0.185	-0.088	-0.297*	-0.276*	-0.298**
	(0.189)	(0.119)	(0.153)	(0.150)	(0.139)
15-19 Days After SIPO	-0.317	-0.221	-0.448**	-0.405**	-0.442***
	(0.216)	(0.158)	(0.174)	(0.175)	(0.161)
20+ Days After SIPO	-0.485**	-0.432**	-0.608***	-0.515***	-0.559***
	(0.204)	(0.214)	(0.180)	(0.180)	(0.176)
N	2188	2056	2056	2056	2057
	(6) *Drop DC*	(7) *Drop CT*	(8) *Drop OR*	(9) *Drop TX*	(10) *Drop MN*
1-5 Days After SIPO[a]	-0.139	-0.141	-0.134	-0.169	-0.128
	(0.103)	(0.102)	(0.107)	(0.104)	(0.102)
6-14 Days After SIPO[a]	-0.298**	-0.301**	-0.296**	-0.344**	-0.287**
	(0.141)	(0.139)	(0.146)	(0.138)	(0.139)
15-19 Days After SIPO	-0.445***	-0.445***	-0.445**	-0.490***	-0.442***
	(0.163)	(0.160)	(0.167)	(0.162)	(0.162)
20+ Days After SIPO	-0.579***	-0.572***	-0.594***	-0.596***	-0.584***
	(0.176)	(0.176)	(0.178)	(0.187)	(0.179)
N	2056	2056	2056	2056	2056

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level.

Notes: Estimates are obtained using weighted least squares regression. The model includes the following controls: an indicator for whether the state had issued a non-essential business closure order (that fell short of a SIPO) or a targeted SIPO for older individuals or those with underlying health conditions, an indicator for whether coverage of local (i.e. city or county) SIPO orders covered at least 50 percent of the state population, an indicator for whether the state had issued restrictions on travel to or from the state, an indicator for whether the state had received a major disaster emergency declaration from the Federal government, the average temperature (in degrees Celsius) in the state, an indicator for whether measurable precipitation fell in the state, state fixed effects, day fixed effects, and a state-specific linear time trend. Standard errors, clustered at the state-level, are reported in parenthesis.

[a] The 99 percent confidence interval for the incubation period for coronavirus is 1 to 14 days (Lauer et al. 2020).

Table 5. Exploring the Effect of SIPOs on COVID-19 Testing and Sensitivity of the Estimated Effect of SIPOs on COVID-19 Cases to Controlling for Testing

	Log (COVID-19 Tests)		*Log (COVID-19 Cases)*	
	(1)	(2)	(3)	(4)
1-5 Days After SIPO[a]	-0.191	-0.316*	-0.132	-0.105
	(0.134)	(0.162)	(0.102)	(0.094)
6-14 Days After SIPO[a]	-0.218	-0.333	-0.281*	-0.248*
	(0.150)	(0.182)	(0.144)	(0.136)
15-19 Days After SIPO	-0.245	-0.321	-0.420**	-0.379**
	(0.185)	(0.217)	(0.164)	(0.151)
20+ Days After SIPO	-0.022	-0.064	-0.547***	-0.522***
	(0.251)	(0.265)	(0.170)	(0.164)
N	2088	2088	2043	2043
State FE, Day FE, State Trends	Yes	Yes	Yes	Yes
State Controls	No	Yes	No	Yes
COVID-19 Testing Control	No	No	No	Yes

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level.

Notes: Estimates are obtained using weighted least squares regression. The model includes the following controls: an indicator for whether the state had issued a non-essential business closure order (that fell short of a SIPO) or a targeted SIPO for older individuals or those with underlying health conditions, an indicator for whether coverage of local (i.e. city or county) SIPO orders covered at least 50 percent of the state population, an indicator for whether the state had issued restrictions on travel to or from the state, an indicator for whether the state had received a major disaster emergency declaration from the Federal government, the average temperature (in degrees Celsius) in the state, an indicator for whether measurable precipitation fell in the state, state fixed effects, day fixed effects, and a state-specific linear time trend. Standard errors, clustered at the state-level, are reported in parenthesis.

[a] The 99 percent confidence interval for the incubation period for coronavirus is 1 to 14 days (Lauer et al. 2020).

Table 6. Difference-in-Difference Estimates of the Effect of SIPOs on Log Daily Cases

	(1)	(2)	(3)	(4)
1-5 Days After SIPO[a]	-0.043	-0.172	-0.097	-0.100
	(0.110)	(0.108)	(0.139)	(0.138)
6-14 Days After SIPO[a]	-0.178	-0.342**	-0.268	-0.272
	(0.182)	(0.149)	(0.177)	(0.174)
15-19 Days After SIPO	-0.392	-0.567***	-0.504**	-0.507**
	(0.246)	(0.191)	(0.220)	(0.219)
20+ Days After SIPO	-0.631	-0.644**	-0.591**	-0.593**
	(0.384)	(0.261)	(0.285)	(0.284)
N	2003	2003	2003	2003
State and Day Fixed Effects	Yes	Yes	Yes	Yes
State Specific Linear Time Trend	Yes	Yes	Yes	Yes
Other COVID-19 Orders	No	Yes	Yes	Yes
Travel Restrictions and Disaster Declaration	No	No	Yes	Yes
Weather Controls	No	No	No	Yes

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level.

Notes: The OLS estimate is weighted using state-level population. Standard errors, clustered at the state-level, are reported in parenthesis. Controls include state and day fixed effects, state-specific linear time trend, an indicator for limited SIPO (non-essential business closure or targeted SIPO), indicator for more than 50% of states covered under county-SIPO order, indicator for travel restriction, indicator for disaster emergency declaration, and weather controls (indicator for any precipitation and average temperature).

[a] The 99 percent confidence interval for the incubation period for coronavirus is 1 to 14 days (Lauer et al. 2020).

Table 7. Sensitivity of Results to the Inclusion of Controls for Census Region- or Census Division-Specific Day Effects

	Log (Cumulative Cases)		*Log (Daily Cases)*	
	(1)	(2)	(3)	(4)
1-5 Days After SIPO	-0.091	-0.070	-0.036	-0.065
	(0.062)	(0.073)	(0.092)	(0.091)
6-14 Days After SIPO	-0.258**	-0.220	-0.221	-0.242
	(0.102)	(0.135)	(0.147)	(0.145)
15-19 Days After SIPO	-0.393***	-0.310*	-0.383*	-0.372**
	(0.144)	(0.179)	(0.197)	(0.179)
20+ Days After SIPO	-0.526**	-0.437*	-0.525*	-0.458**
	(0.205)	(0.225)	(0.279)	(0.229)
N	2100	2100	2003	2003
Region-Specific Time Effects?	Yes	No	Yes	No
Census Division-Specific Time Effects'	No	Yes	No	Yes

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level.

Notes: Estimates are obtained using weighted least squares regression. The model includes the following controls: an indicator for whether the state had issued a non-essential business closure order (that fell short of a SIPO) or a targeted SIPO for older individuals or those with underlying health conditions, an indicator for whether coverage of local (i.e. city or county) SIPO orders covered at least 50 percent of the state population, an indicator for whether the state had issued restrictions on travel to or from the state, an indicator for whether the state had received a major disaster emergency declaration from the Federal government, the average temperature (in degrees Celsius) in the state, an indicator for whether measurable precipitation fell in the state, state fixed effects, day fixed effects, and a state-specific linear time trend. Standard errors, clustered at the state-level, are reported in parenthesis.

[a] The 99 percent confidence interval for the incubation period for coronavirus is 1 to 14 days (Lauer et al. 2020).

Table 8. Negative Binominal Estimates of the Effect of SIPOs on Deaths

	(1)	(2)	(3)	(4)
1-5 Days After SIPO	-0.037	-0.053	-0.038	-0.147
	(0.130)	(0.168)	(0.175)	(0.116)
6-14 Days After SIPO	-0.195	-0.249	-0.154	-0.240
	(0.235)	(0.231)	(0.283)	(0.211)
15-19 Days After SIPO	-0.336	-0.430	-0.286	-0.366
	(0.366)	(0.319)	(0.354)	(0.287)
20+ Days After SIPO	-0.637	-0.770	-0.305	-0.383
	(0.560)	(0.478)	(0.335)	(0.289)
N	2156	2156	2156	2156
State FE, Day FE	Yes	Yes	Yes	Yes
State Controls	No	Yes	No	Yes
State Specific Linear Time Trend?	No	No	Yes	Yes

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level.

Notes: Estimates are obtained using weighted least squares regression. The model includes the following controls: an indicator for whether the state had issued a non-essential business closure order (that fell short of a SIPO) or a targeted SIPO for older individuals or those with underlying health conditions, an indicator for whether coverage of local (i.e. city or county) SIPO orders covered at least 50 percent of the state population, an indicator for whether the state had issued restrictions on travel to or from the state, an indicator for whether the state had received a major disaster emergency declaration from the Federal government, the average temperature (in degrees Celsius) in the state, an indicator for whether measurable precipitation fell in the state, state fixed effects, day fixed effects, and a state-specific linear time trend. Standard errors, clustered at the state-level, are reported in parenthesis.

Table 9A. Heterogeneity in Health Effects of SIPOs by Earlier and Later Adopting States

	(1) Log(Cases)	(2) Deaths
Early Adopting States * 1-5 Days After SIPO	-0.267**	-0.296
	(0.123)	(0.163)
Early Adopting States * 6-14 Days After SIPO	-0.582***	-0.609**
	(0.190)	(0.248)
Early Adopting States * 15-19 Days After SIPO	-0.901***	-0.860***
	(0.265)	(0.326)
Early Adopting States * 20+ Days After SIPO	-1.087***	-0.900**
	(0.353)	(0.390)
Late Adopting States * 1-5 Days After SIPO	-0.137	-0.095
	(0.089)	(0.132)
Late Adopting States * 6-14 Days After SIPO	-0.257	-0.040
	(0.157)	(0.229)
Late Adopting States * 15-19 Days After SIPO	-0.254	-0.000
	(0.223)	(0.324)
Late Adopting States * 20+ Days After SIPO	-0.151	0.048
	(0.275)	(0.392)
N	2100	2156

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level.

Notes: The OLS estimate is weighted using state-level population. Standard errors, clustered at the state-level, are reported in parenthesis. Controls include state and day fixed effects, state-specific linear time trend, an indicator for limited SIPO (non-essential business closure or targeted SIPO), indicator for more than 50% of states covered under county-SIPO order, indicator for travel restriction, indicator for disaster emergency declaration, and weather controls (indicator for any precipitation and average temperature). States that enacted SIPO between March 19 and 25 are coded as early adopting states. States that enacted SIPO on March 26 or later are coded as late adopting states.

Table 9B: Examination of Heterogeneous Treatment Effects by Population Density of SIPO-Adopting State

	(1) Log Cases	(2) Deaths
1-5 Days After SIPO * Lower 25th Percentile Population Density	-0.200*	0.077
	(0.114)	(0.305)
1-5 Days After SIPO * Middle 50th Percentile Population Density	-0.086	-0.174
	(0.093)	(0.138)
1-5 Days After SIPO * Upper 25th Percentile Population Density	-0.182	-0.083
	(0.130)	(0.220)
6-14 Days After SIPO * Lower 25th Percentile Population Density	-0.237	0.127
	(0.196)	(0.478)
6-14 Days After SIPO * Middle 50th Percentile Population Density	-0.214	-0.373*
	(0.155)	(0.224)
6-14 Days After SIPO * Upper 25th Percentile Population Density	-0.344**	-0.044
	(0.145)	(0.379)
15-19 Days After SIPO * Lower 25th Percentile Population Density	-0.295	0.218
	(0.257)	(0.689)
15-19 Days After SIPO * Middle 50th Percentile Population Density	-0.337*	-0.625**
	(0.200)	(0.309)
15-19 Days After SIPO * Upper 25th Percentile Population Density	-0.491***	-0.080
	(0.171)	(0.500)
20+ Days After SIPO * Lower 25th Percentile Population Density	-0.258	0.358
	(0.377)	(0.805)
20+ Days After SIPO * Middle 50th Percentile Population Density	-0.585**	-0.775*
	(0.271)	(0.427)
20+ Days After SIPO * Upper 25th Percentile Population Density	-0.533**	-0.000
	(0.242)	(0.508)
N	2100	2162

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level.

Notes: Weighted least squares estimates are shown in table. Standard errors, clustered at the state-level, are reported in parenthesis. Controls include state and day fixed effects, state-specific linear time trend, an indicator for limited SIPO (non-essential business closure or targeted SIPO), indicator for more than 50% of states covered under county-SIPO order, indicator for travel restriction, indicator for disaster emergency declaration, and weather controls (indicator for any precipitation and average temperature).

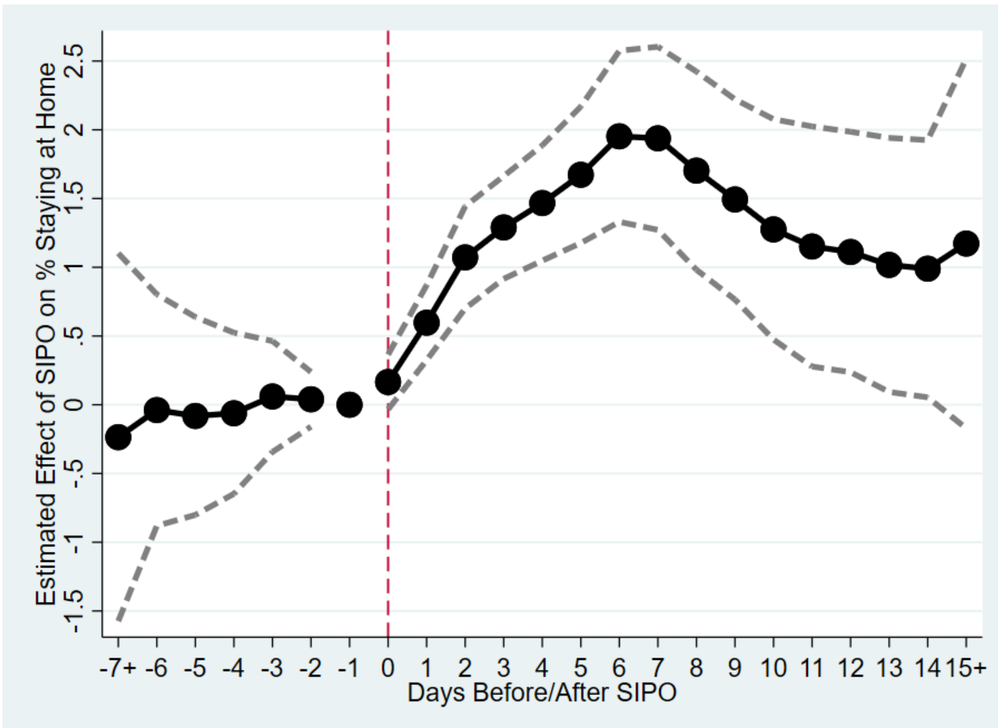
Table 9C: Examination of Heterogeneous Treatment Effects on Social Distancing by Timing of SIPO Adoption and Population Density

	Panel I: Earlier and Later Adopting States
Early Adopting States*SIPO	2.585***
	(0.361)
Late Adopting States*SIPO	1.335***
	(0.353)
	Panel II: Population Density
SIPO* Lower 25th Percentile Population Density	0.436
	(0.724)
SIPO* Middle 50th Percentile Population Density	1.855***
	(0.401)
SIPO* Upper 25th Percentile Population Density	2.559***
	(0.430)
	(0.674)
N	2091

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level.

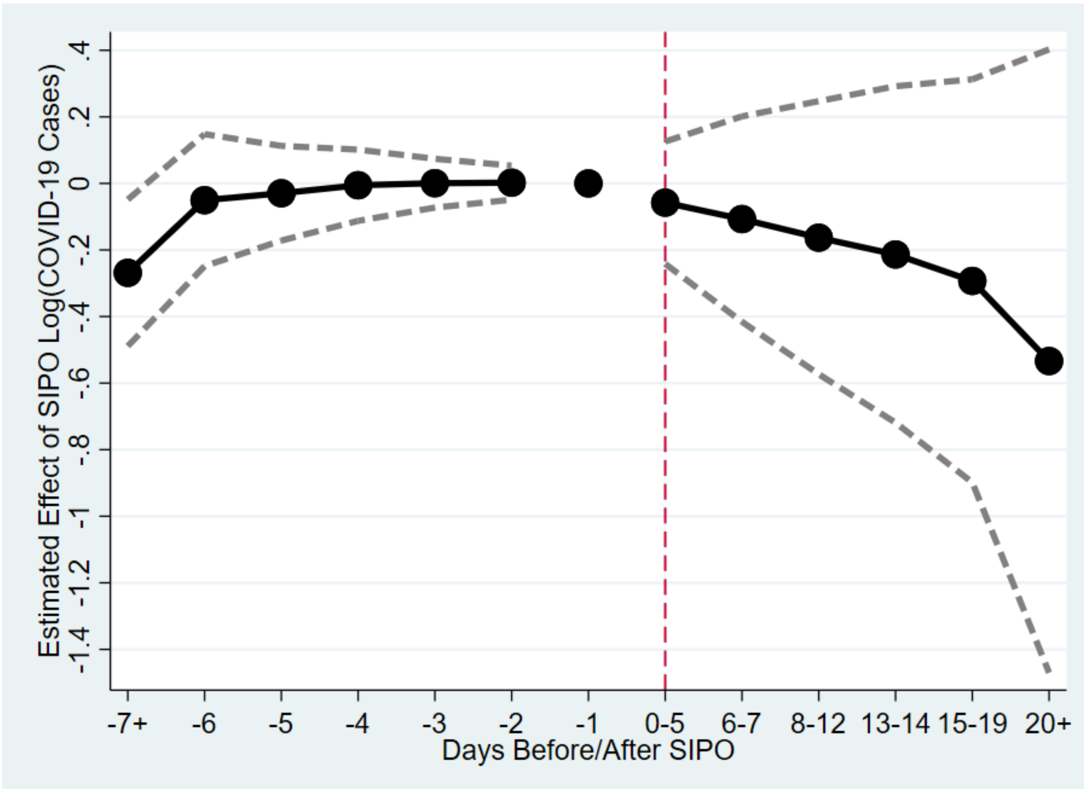
Notes: The OLS estimate is weighted using state-level population. Standard errors, clustered at the state-level, are reported in parenthesis. Controls include state and day fixed effects, state-specific linear time trend, an indicator for limited SIPO (non-essential business closure or targeted SIPO), indicator for more than 50% of states covered under county-SIPO order, indicator for travel restriction, indicator for disaster emergency declaration, and weather controls (indicator for any precipitation and average temperature). States that enacted SIPO between March 19 and 25 are coded as early adopting states. States that enacted SIPO on March 26 or later are coded as late adopting states.

Appendix Figure 1: Event-Study Analysis of Shelter in Place Orders (SIPOs) and Percent Staying at Home: Restricting Our Samples to States with More than 15 Days of Post-Treatment Data



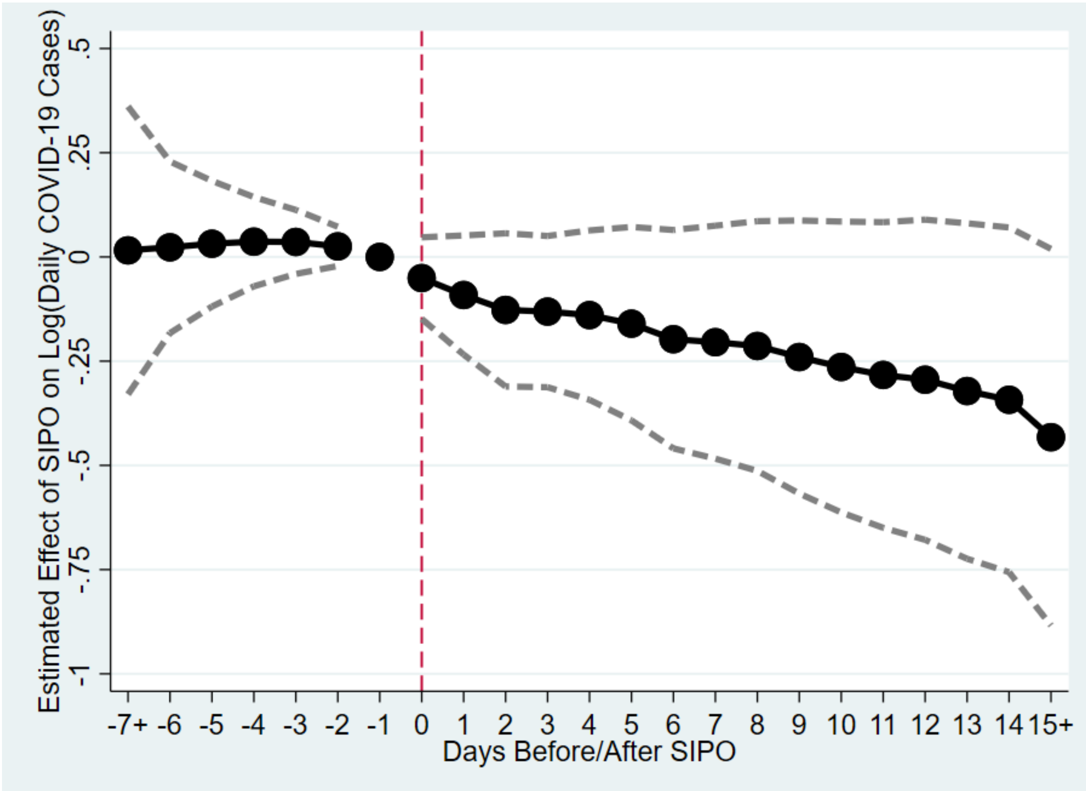
Notes: Estimates are obtained using weighted least squares regression. The model includes controls for state fixed effects, day fixed effects, and state-specific linear pre-trends. Standard errors are clustered at the state level.

Appendix Figure 2: Event Studies Analysis on Log (COVID-19 Cases) for Two-Way Fixed Effects Model



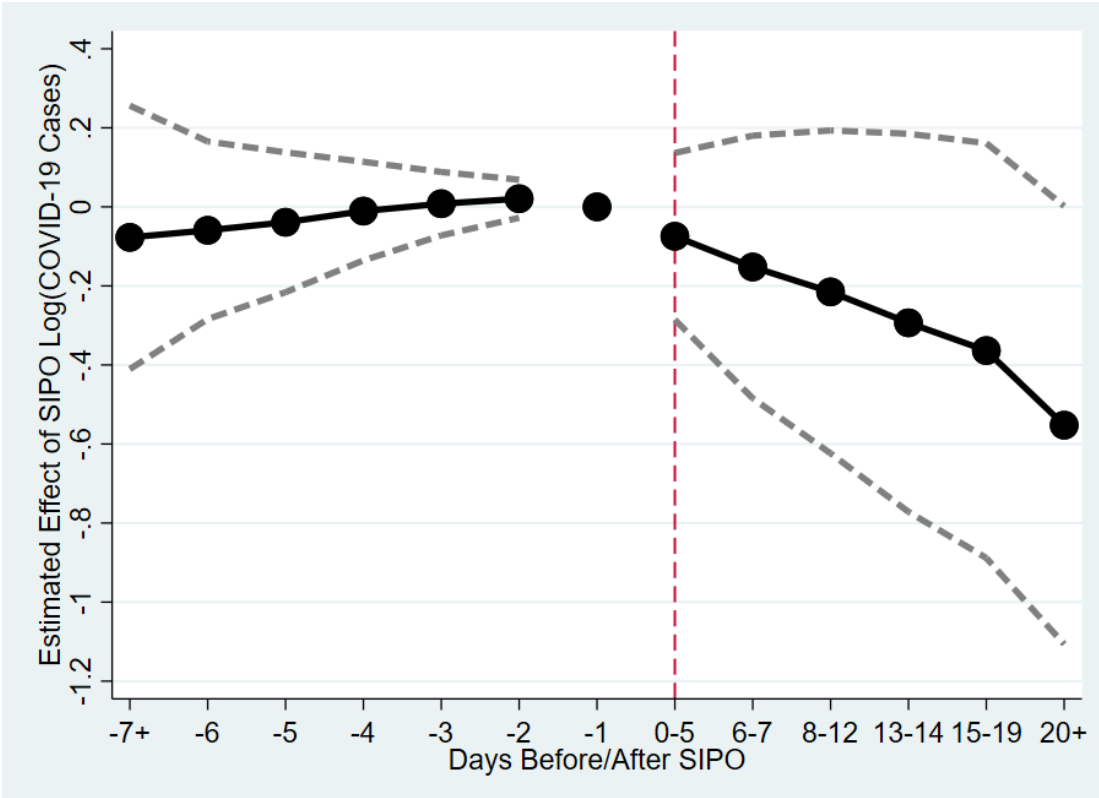
Notes: Estimates are obtained using weighted least squares regression. The model includes controls for state fixed effects, day fixed effects, state-specific linear time trends, and the controls listed in Appendix Table 1. Standard errors are clustered at the state level.

Appendix Figure 3: Event-Study Analysis of SIPOs and Log (COVID-19 Cases) Using Individual Pre- and Post-Treatment Days



Notes: Estimates are obtained using weighted least squares regression. The model includes controls for state fixed effects, day fixed effects, state-specific linear time trends, and the controls listed in Appendix Table 1. Standard errors are clustered at the state level.

Appendix Figure 4: Event Studies Analysis of SIPOs and Log (COVID-19 Cases) Including New York & New Jersey



Notes: Estimates are obtained using weighted least squares regression. The model includes controls for state fixed effects, day fixed effects, state-specific linear time trends, and the controls listed in Appendix Table 1. Standard errors are clustered at the state level.

Appendix Table 1. Descriptive Statistics

	(1) Full Sample	(2) State-Day w/o SIPO	(3) State-Day w/ SIPO
Dependent Variables			
Percent at Home	35.694	28.715	42.285
	(9.406)	(7.160)	(3.946)
Cases per 100,000	45.920	15.059	77.271
	(72.477)	(52.476)	(76.454)
Daily Cases per 100,000	3.360	1.620	5.128
	(4.768)	(3.822)	(4.980)
Testing per 100,000	363.822	132.513	589.514
	(421.622)	(307.688)	(394.689)
Deaths per 100,000	1.569	0.400	2.757
	(3.385)	(1.956)	(4.052)
Independent Variables			
SIPO	0.496	0.000	1.000
	(0.500)	(-)	(-)
NEBCO or Targeted SIPO	0.121	0.241	0.000
	(0.327)	(0.428)	(-)
Local SIPO Covering 50% of Population	0.043	0.085	0.000
	(0.203)	(0.279)	(-)
Disaster Emergency Declaration	0.541	0.201	0.886
	(0.498)	(0.401)	(0.318)
Travel Restriction	0.157	0.108	0.207
	(0.364)	(0.310)	(0.405)
Any Measurable Precipitation	0.772	0.763	0.781
	(0.420)	(0.425)	(0.414)
Average Temperature	10.604	10.697	10.509
	(6.782)	(7.306)	(6.208)

Notes: Means are weighted using the state population

Appendix Table 2. Date of First Confirmed COVID-19 Case and Death, by State

State	Case	Death	State	Case	Death
Washington	1/21/2020	2/29/2020	Oklahoma	3/6/2020	3/19/2020
Illinois	1/24/2020	3/17/2020	Pennsylvania	3/6/2020	3/18/2020
California	1/25/2020	2/6/2020*	South Carolina	3/6/2020	3/16/2020
Arizona	1/26/2020	3/20/2020	Kansas	3/7/2020	3/12/2020
Massachusetts	2/1/2020	3/20/2020	Missouri	3/7/2020	3/18/2020
Wisconsin	2/5/2020	3/19/2020	Vermont	3/7/2020	3/19/2020
Texas	2/12/2020	3/16/2020	Virginia	3/7/2020	3/14/2020
Nebraska	2/17/2020	3/27/2020	Connecticut	3/8/2020	3/18/2020
Utah	2/25/2020	3/22/2020	Iowa	3/8/2020	3/24/2020
Oregon	2/28/2020	3/14/2020	Louisiana	3/9/2020	3/14/2020
Florida	3/1/2020	3/6/2020	Ohio	3/9/2020	3/20/2020
New York	3/1/2020	3/14/2020	Michigan	3/10/2020	3/18/2020
Rhode Island	3/1/2020	3/28/2020	South Dakota	3/10/2020	3/10/2020
Georgia	3/2/2020	3/12/2020	Arkansas	3/11/2020	3/24/2020
New Hampshire	3/2/2020	3/23/2020	Delaware	3/11/2020	3/26/2020
North Carolina	3/3/2020	3/25/2020	Mississippi	3/11/2020	3/19/2020
New Jersey	3/4/2020	3/10/2020	New Mexico	3/11/2020	3/25/2020
Colorado	3/5/2020	3/12/2020	North Dakota	3/11/2020	3/27/2020
Maryland	3/5/2020	3/18/2020	Wyoming	3/11/2020	4/13/2020
Nevada	3/5/2020	3/16/2020	Alaska	3/12/2020	3/27/2020
Tennessee	3/5/2020	3/21/2020	Maine	3/12/2020	3/27/2020
Hawaii	3/6/2020	3/31/2020	Alabama	3/13/2020	3/25/2020
Indiana	3/6/2020	3/16/2020	Idaho	3/13/2020	3/26/2020
Kentucky	3/6/2020	3/16/2020	Montana	3/13/2020	3/27/2020
Minnesota	3/6/2020	3/21/2020	West Virginia	3/17/2020	3/29/2020

Source: State and local health agencies and hospitals.
* This case was not recognized as a COVID-19 death at the time, but was confirmed weeks later via tissue samples from the deceased.

Appendix Table 3: Difference-in-Difference Estimates of the Effect of SIPOs on Log (COVID-19 Cases

	(1)	(2)	(3)	(4)	(5)
1-5 Days After SIPO[a]	0.035	-0.146	-0.160	-0.143	-0.137
	(0.114)	(0.116)	(0.126)	(0.109)	(0.103)
6-14 Days After SIPO[a]	-0.086	-0.329*	-0.350*	-0.309*	-0.295**
	(0.235)	(0.170)	(0.180)	(0.157)	(0.141)
15-19 Days After SIPO	-0.214	-0.475**	-0.498**	-0.461**	-0.440***
	(0.331)	(0.193)	(0.203)	(0.184)	(0.162)
> 19 Days After SIPO	-0.473	-0.599***	-0.626***	-0.597***	-0.575***
	(0.495)	(0.193)	(0.204)	(0.190)	(0.176)
NEBCO or Targeted SIPO			0.019	0.017	0.016
			(0.085)	(0.091)	(0.088)
Local SIPO Covering 50% of Population			-0.085	-0.029	-0.041
			(0.111)	(0.096)	(0.095)
Disaster Emergency Declaration				-0.167**	-0.170**
				(0.071)	(0.072)
Travel Restriction				0.070	0.095*
				(0.056)	(0.055)
Average Temperature					0.008**
					(0.003)
Any Measurable Precipitation					-0.004
					(0.013)
N	2100	2100	2100	2100	2100
State and Day Fixed Effects	Yes	Yes	Yes	Yes	Yes
State Specific Linear Time Trend	No	Yes	Yes	Yes	Yes
Other COVID-19 Orders	No	No	Yes	Yes	Yes
Travel Restrictions and Disaster Declaration	No	No	No	Yes	Yes
Weather Controls	No	No	No	No	Yes

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level.

Notes: Estimates are obtained using weighted least squares regression. The model includes the following controls: an indicator for whether the state had issued a non-essential business closure order (that fell short of a SIPO) or a targeted SIPO for older individuals or those with underlying health conditions, an indicator for whether coverage of local (i.e. city or county) SIPO orders covered at least 50 percent of the state population, an indicator for whether the state had issued restrictions on travel to or from the state, an indicator for whether the state had received a major disaster emergency declaration from the Federal government, the average temperature (in degrees Celsius) in the state, an indicator for whether measurable precipitation fell in the state, state fixed effects, day fixed effects, and a state-specific linear time trend. Standard errors, clustered at the state-level, are reported in parenthesis.

[a] The 99 percent confidence interval for the incubation period for coronavirus is 1 to 14 days (Lauer et al. 2020).

Appendix Table 4: Difference-in-Difference Estimates of the Effect of Non-Essential Business Closures on Log (COVID-19 Cases)

	(1)
1-5 Days After NEBCO	0.003
	(0.084)
6-14 Days After NEBCO	0.023
	(0.100)
15-19 Days After NEBCO	0.054
	(0.118)
> 19 Days After NEBCO	0.219
	(0.242)
N	1855

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level.

Notes: Estimates are obtained using weighted least squares regression. The model includes the following controls: an indicator for whether the state had issued a shelter in place order, an indicator for whether coverage of local (i.e. city or county) SIPO orders covered at least 50 percent of the state population, an indicator for whether the state had issued restrictions on travel to or from the state, an indicator for whether the state had received a major disaster emergency declaration from the Federal government, the average temperature (in degrees Celsius) in the state, an indicator for whether measurable precipitation fell in the state, state fixed effects, day fixed effects, and a state-specific linear time trend. Standard errors, clustered at the state-level, are reported in parenthesis.
[a] The 99 percent confidence interval for the incubation period for coronavirus is 1 to 14 days (Lauer et al. 2020).