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ABSTRACT

On March 19, 2020, California Governor Gavin Newsom issued Executive Order N-33-20 2020, which required all residents of the state of California to shelter in place for all but essential activities such as grocery shopping, retrieving prescriptions from a pharmacy, or caring for relatives. This shelter-in-place order (SIPO), the first such statewide order issued in the United States, was designed to reduce COVID-19 cases and mortality. While the White House Task Force on the Coronavirus has credited the State of California for taking early action to prevent a statewide COVID-19 outbreak, no study has examined its impact. This study is the first to estimate the effect of SIPO adoption on health. Using daily state-level coronavirus data and a synthetic control research design, we find that California’s statewide SIPO reduced COVID-19 cases by 125.5 to 219.7 per 100,000 population by April 20, one month following the order. We further find that California’s SIPO led to as many as 1,661 fewer COVID-19 deaths during this period. Back-of-the-envelope calculations suggest that there were about 400 job losses per life saved during this short-run post-treatment period.

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1. Motivation

"I simply do not know if our aggressive actions early on ... have had the intended effect … I certainly am hoping and praying that that is the case. We still need the data to confirm that."

- Grant Colfax, San Francisco Director of Public Health, March 31, 2020

The 2020 U.S. coronavirus outbreak is one of the most serious public health challenges in American history. The U.S. has seen more reported COVID-19 cases between January 1, 2020 and April 16, 2020 than reported polio cases between 1910 and 2010 (Ochmann and Roser 2020). The transmission of COVID-19 is presently believed to occur largely through exposure to respiratory droplets, usually emitted during coughing, sneezing, or nose-blowing (Centers for Disease Control and Prevention 2020a), but may also occur through natural respiratory expulsion (Fineberg 2020). The primary strategies suggested by governments worldwide to reduce the spread of COVID-19 have been frequent handwashing, mask-wearing in public, and social distancing (Australian Government Department of Health 2020; Public Health England 2020; Public Health Agency of Canada 2020; White House 2020).

In contrast to many countries throughout the world, many of the authorities used to combat public health threats in the United States rest not with the Federal government, but largely with state and local officials. The primary state and local policy strategy to prevent the spread of coronavirus is the enactment of shelter-in-place orders (SIPOs), sometimes called "stay at home" orders. The State of California was at the forefront of issuing comprehensive SIPOs as the COVID-19 crisis unfolded nationwide. On March 17 and 18, 2020, 12 California counties and the City of Berkeley adopted SIPOs.[1] And on the evening of March 19, Governor Gavin Newsom announced the nation's first statewide SIPO, earning immediate attention in the national news media. California Executive Order N-33-20 2020 stated:

> "To protect public health, I as State Public Health Officer and Director of the California Department of Public Health order all individuals living in the State of California to stay home or at their place of residence except as needed to maintain continuity of operations of the federal critical infrastructure sectors…" (California Executive Order N-33-20 2020).

This statewide executive order required all California 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. While grocery stores, pharmacies, restaurants providing takeout or delivery service, and other essential businesses were permitted to remain open, most other non-essential businesses were ordered closed.[2] In addition, residents were advised to continue to maintain a six-foot distance with non-household members with whom they come in contact and public gatherings of non-household members were strongly discouraged.

Violations of the SIPO were subject to a $1,000 fine and up to 6 months of imprisonment (Allday 2020), though enforcement most often occurred through social pressure and warnings for

[1] On March 16, Los Angeles Mayor Eric Garcetti implemented a non-essential business closure order. The seven counties that adopted a SIPO on March 17 were: Alameda, Contra Costa, Mendocino, San Francisco, San Mateo, Santa Clara, and Santa Cruz. The five counties that adopted a SIPO on March 18 were: Monterey, San Benito, Solano, Sonoma, and Ventura.

[2] California's statewide SIPO was soon followed by the closing of many public parks or beaches (California Department of Parks and Recreation 2020), driven in part by public outrage over the surge in beach parties and picnics immediately following the executive order (Kopetman 2020).

first offenses. State SIPOs appear to have had increased social distancing (Abouk and Heydari 2020; Fry 2020), with non-essential travel falling 40 to 60 percent following California's SIPO (COVID-19 Community Mobility Report).

In issuing the SIPO, Governor Newsom implored residents of California "to meet this moment and flatten the curve together" (Romero 2020). Thus, an important policy rationale was not simply to curb the pandemic's growth in California, but also to delay its peak, allowing the state additional time to obtain the necessary ventilators, hospital beds, and medical staff in place to meet the surge in demand for services among those who test positive (Baker and Fink 2020; Greenstone and Nigam 2020; Ranney et al. 2020; Tsai et al. 2020; Hicks and Marsh 2020).

The White House Coronavirus Task Force singled out two states, including California, for their early adoption of mandatory social distancing policies:

> "[Dr. Deborah] Birx said the experiences of California and Washington give her hope that other states can keep the coronavirus under control through social distancing. That's because they moved quickly to contain the early clusters of coronavirus by closing schools, urging people to work from home, banning large gatherings and taking other measures now familiar to most Americans." (The Associated Press, March 31, 2020)

Following the adoption of California's SIPO, 40 additional states and the District of Columbia enacted similar statewide SIPOs between March 20, 2020 and April 20, 2020. And by early April, over 90 countries worldwide, representing half of the world's population, requested or ordered their citizens to stay at home (Sandford 2020).

There are a number of important reasons to single out California's SIPO in studying its effects on COVID-19 infection and mortality. First, California was the first state to implement a statewide order, an important policy feature designed to prevent within-state spillovers of infectious disease across neighboring counties, cities, and townships with heterogeneous local orders. Second, California ranks 12 out of 51 states (including the District of Columbia) in population per square mile (World Population Review) and 2 out of 51 in percent living in urbanized areas and urban clusters (Iowa Community Indicators Program).[3] The spread of coronavirus is exacerbated by increased population density, which generates greater opportunities for transmission among frequently interacting individuals (Centers for Disease Control and Prevention 2020b). This makes California a location with a high potential for rapid spread of the disease.

Third, California implemented its SIPO at a unique time: early in the cycle of an outbreak, when the rate of growth in observed coronavirus case rates was quite low relative to other states that ultimately implemented SIPOs. The average daily growth in confirmed coronavirus cases in the four days prior to SIPO enactment was 19.1 percent in California. No other SIPO-implementing state in the upper 25th percentile of the state population density or urbanicity distribution had an average daily coronavirus growth rate lower than California during this period. As a comparison, New York, which had the highest per-capita case rate in the nation throughout much of the outbreak, had an average daily coronavirus case growth rate of 39.5 percent in the four days prior to its enactment of a SIPO. In this context, California may provide a cleaner natural experiment in relation to later adopters, while also informing the efficacy of the decision to enact a SIPO early in the outbreak cycle. Finally, at this early stage of assessing the

[3] In 2019, the population density in California was 253.7 persons per square mile; 95.0 percent of residents lived in an urbanized area or urban cluster.

short-run public health effects of SIPOs, California has more days of post-treatment data than any other state, critical for analyzing the public health benefits of an epidemic with potentially exponential short-run contagion and lagged mortality effects.

While there is speculation by the White House Coronavirus Task Force that SIPOs have been effective at "bending the case curve," there is little rigorous empirical analysis of this question. This study is the first to examine early public health effects of a statewide SIPO.

Using 40 days of state-level data on confirmed COVID-19 cases and COVID-19-related deaths, this study provides evidence on the public health effects of California's SIPO during the crucial early weeks of the policy. Estimates from our preferred synthetic control models show that California's SIPO led to a 125.5 to 219.7 per 100,000 population reduction in COVID-19 cases and a 1.9 to 4.2 per 100,000 population reduction in COVID-19-related deaths per 100,000 during the first month following its enactment. These findings are robust to the selection of observables (i.e. pre-treatment COVID-19 rates, population density, urbanicity, and other COVID-related policies) to generate the weights to construct our counterfactual. We find that the number of cases averted and lives saved were much larger in the second and third weeks following the SIPO's adoption, consistent with growing public health benefits over the period during which the outbreak was exponentially growing. Back-of-the-envelope calculations suggest that there were approximately 8 to 14 job losses per coronavirus case averted and 421 to 917 job losses per life saved during this short-run post-SIPO window in California.

2. Background on Coronavirus

In December 2019, an outbreak of a new zoonotic coronavirus, SARS-CoV-2, which causes the disease COVID-19, was detected in Wuhan, Hubei Province, China (World Health Organization 2020a). The symptoms of COVID-19 resemble that of influenza, including fever, cough, and shortness of breath (Centers for Disease Control and Prevention 2020c). However, severe respiratory symptoms generate a mortality rate that may be an order of magnitude greater than that of the common flu (World Health Organization 2020b, House Oversight and Reform Committee 2020). Deaths from COVID-19-related illness are heavily concentrated among the elderly and those with underlying health conditions such as respiratory ailments, heart disease, diabetes, or high blood pressure (Wu and McGoogan 2020; Verity et al. 2020; CDC Covid-19 Response Team 2020).

The substantial epidemiological risk from this new coronavirus is exacerbated by (i) a high degree of contagion (Thackeray 2020; Cascella et al. 2020), (ii) the possibility that transmission may occur among those who are asymptomatic (Centers for Disease Control and Prevention 2020a; Mandavilli 2020, Whitehead 2020, Li et al. 2020), and (iii) lack of adequate testing (Cohen 2020, Shear et al. 2020, Rabin et al. 2020, Desiderio and Levine 2020). In the main, transmission of COVID-19 occurs via respiratory droplets, usually emitted during coughing, sneezing, or nose-blowing (Centers for Disease Control and Prevention 2020a, World Health Organization 2020c & 2020d). There is also some evidence that the disease may be easily transmitted through normal breathing function in common air space (Fineberg 2020). The incubation period for COVID-19 is 2 to 14 days, during which time transmission may also be possible (Centers for Disease Control and Prevention 2020b, Li et al. 2020).

U.S. pharmaceutical companies, in partnership with the public sector, have begun clinical trials for a COVID-19 vaccine (White House 2020, Food and Drug Administration 2020). However, a longer-run medical solution such as a vaccine is unlikely to solve short-run capacity constraints faced by hospitals, which have faced a sharp increase in demand for medical services among coronavirus patients (Secon 2020, Seewer 2020, Kaste 2020, Marquez and Moghe 2020).

Fears over shortages of ventilators (Baker and Fink 2020, Ranney et al. 2020), intensive care unit beds (Tsai et al. 2020, Hicks and Marsh 2020), and protective personal equipment (James 2020, Petras and Loehrke 2020, Ranney et al. 2020, World Health Organization 2020e) have instead led policymakers to seek strategies to "flatten the curve" of infections, reducing the peak number of infections and spreading its incidence over time (Meredith 2020). The World Health Organization (WHO) recommended that individuals frequently wash hands, avoid shaking hands with others, self-isolate when presenting flu-like symptoms, and avoid all unnecessary contact with non-household members through the practice of social distancing (World Health Organization 2020b). The adoption of shelter-in-place orders is the dominant policy strategy to induce such distancing.

SIPOs can affect COVID-19 cases and deaths through a number of channels. As public health officials and epidemiologists expect, reducing exposure of uninfected individuals to those who are infected via social distancing should reduce the transmission rate of the virus. However, there are other indirect channels through which SIPOs could impact reported cases and deaths. SIPOs may affect testing and coronavirus-related mortality because infected individuals who are unaware of their infection choose to stay at home rather than seek out testing or other medical care. This may be because of fears of contagion at medical facilities or because of a desire to adhere to a "civic duty" to shelter in place. In addition, as SIPOs may necessitate an increase in public resources spent on patrol and enforcement, they may reduce resources available for public health services. On the other hand, as SIPOs are expected to reduce the demand for "non-essential" medical procedures such as well care visits or elective surgery, they may free up resources for those most at risk for coronavirus-related mortality.

3. Data and Methodology

3.1 Data

In order to examine the "first stage" compliance with the California SIPO, we utilize publicly available data from SafeGraph Inc.[4] For each state (and county) on each day SafeGraph provides a shelter-in-place index, based on the percent of individuals staying at home during the day. The metric is calculated from spatial data generated using anonymous cell phone pings. First, each cell phone is assigned a "home" (or 153m by 153m square) based on a common nighttime location over a baseline period. SafeGraph then calculates the percent staying at home, i.e. the fraction of cell phones in a geographic unit (state, county, etc.) that do not leave the "home" for any given day.[5] The shelter-in-place index is the percentage point change in the number of cell phones staying at home relative to the baseline of February 6, 2020 through February 12, 2020.[6]

To examine the short-run public health effects of the statewide order, we utilize a panel of state-specific daily counts of COVID-19 cases and deaths from March 12, 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.[7] As of April 20, there were a total of 778,328 confirmed COVID-19 cases in the United States, 4.3 percent (33,862) of which were in California, and 37,372 coronavirus-related deaths, 3.2 percent (1,223) of which were in California.

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[4] Data and detailed descriptions of variable construction are available at: https://www.safegraph.com/dashboard/covid19-shelter-in-place

[5] SafeGraph makes adjustments for small geographic units which are not relevant for a state-level analysis.

[6] So a value of 25 is for the shelter in place index could represent an increase from of 12% of phones staying at home at baseline to 37% of phones staying at home (37-12=25).

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

Figure 1 shows state-specific trends in cumulative coronavirus rates per 100,000 population in each state. Daily cases can be calculated as the slope of this cumulative case distribution. Over the period under study, the average coronavirus case rate in California was 30.8 per 100,000 population, and its growth rate from March 12 to April 20 ranked 6th lowest among the 50 states and the District of Columbia. In addition, California had the lowest case growth rate among the top 25th percentile of most highly urbanized states. California also had the lowest case rate among the top 25th percentile of most highly densely populated states.

Figure 2 shows the trends in cumulative coronavirus-related death rates per 100,000 population. Between March 12 and April 20, the COVID-19 death rate in the United States grew by 8.56 deaths per 100,000 population, while it grew by less than one half as much (3.08 per 100,000 population) in California. New York, New Jersey, Washington, Louisiana, and Massachusetts had among the highest rates of coronavirus-related deaths at the end of the sample period. In terms of the death rate, the growth in the COVID-19 death rate in California ranked lowest among the top 25th percentile of most highly urbanized states.

Figure 3 shows trends in coronavirus case rates for each county in the state of California during the sample period. As noted above, prior to the statewide SIPO on March 19, 12 counties and the City of Los Angeles adopted SIPOs. Early adopting counties are shaded black and all other counties are shaded gray. We find that the growth rate in coronavirus cases from March 12 through April 20 in early adopting California counties was about 9 percent. This compares to an average growth rate of 11 percent in the remaining counties in the state who were bound by the statewide order.[8]

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[8] Appendix Figure 1 shows trends in coronavirus mortality rates for each county in California during the sample period. Due to many low population counties with zero deaths for much of the sample period it is difficult to draw reliable inference with regards to county level SIPOs and mortality.

3.2 Synthetic Control Design

We use the synthetic control method introduced by Abadie et al. (2010) to infer the causal impact of SIPOs on the number of confirmed coronavirus cases and number of COVID-19-related deaths per 100,000 population in California. This method uses data on pre-treatment COVID-19 case (or mortality) rates and observable characteristics of states that may influence the spread of the virus (i.e. population density, urbanicity, emergency decrees for major disaster area, travel restrictions, and the number of tests conducted).[9] The synthetic control approach generates a counterfactual designed to capture how coronavirus cases would have evolved in California in the absence of its SIPO.

Our chief outcomes of interest, $Case\ Rate_{it}$ and $Death\ Rate_{it}$, measure the cumulative number of confirmed coronavirus cases and number of coronavirus-related deaths per 100,000 population in state *i* at day *t*. We estimate the unobserved counterfactual ("synthetic California") as a weighted linear combination of states included in a donor pool. The weights are chosen so as to generate a synthetic state that is as similar as possible to California on key observables. Given the importance of the selection (i) of states to be included in the donor pool, and (ii) observable characteristics on which to closely match California to its synthetic counterpart, it is

[9] Population density is measured as the ratio of state population to land area in square miles and is available from U.S. Census (see: https://www.census.gov/geographies.html). Urbanicity is measured as percentage of total population living in urban areas and is available from Iowa Community Indicators Program (see: https://www.icip.iastate.edu/tables/population/urban-pct-states). Emergency major disaster declarations are measured as a state with disaster that exceeds the response capabilities of the state and local governments, and long-term recovery assistance is needed and are available from the Federal Emergency Management Agency (see: https://www.fema.gov/disasters). Travel restrictions are measured as states that restrict residents from traveling to other states and/or states that restrict residents of other states from entering the state. COVID-19 tests are measured as the natural log of total coronavirus tests reported by each state. These data are available from COVID Tracking Project (see: https://covidtracking.com).

incumbent on researchers to offer a theoretical defense of these choices and to explore the sensitivity of estimated policy impacts to these choices (Ferman 2019).

Our primary donor pool is comprised of a total of 42 state and the District of Columbia: 10 states that had never enacted a SIPO during our sample period, and 32 states and the District of Columbia that adopted a SIPO at least 5 days after California did so. We select this five-day period because it is the median incubation period of COVID-19 (Lauer et al. 2020), and thus gives the case data from California sufficient time to reflect underlying changes in the transmission rate before any of the donor states implement their own SIPOs. Coupled with information on the date at which each state implemented a SIPO (Appendix Table 1), our decision rule eliminates the following states from our donor pool: Illinois, New Jersey, New York, Connecticut, Louisiana, Oregon, and Washington.[10] Moreover, as shown in Figures 1 and 2, several of these states (New Jersey, New York, and Washington) appeared to be on very different pre-treatment case and mortality trends than the majority of states, including California. To test the sensitivity of our results to the inclusion of these 43 states (including the District of Columbia) in the donor pool, we re-estimate our synthetic control models without eliminating pre-March 24 SIPO-adopters from the donor pool. Our main findings are largely unchanged (see column 1 of Appendix Table 2).

One limitation to our preferred donor pool is that by including later-adopting SIPO states as potential donors, the synthetic control is contaminated on some post-treatment days. Thus, to the extent that later enacted SIPOs have taken effect, our estimated treatment effects will be biased towards zero and lower-bound estimates. As one approach to address this concern, we

[10] Ohio implemented its statewide SIPO at 11:59pm on March 23, 2020. We code this order as effective on March 24, 2020. However, if we exclude Ohio from our donor pool, we obtain a pattern of results quantitatively similar to those reported above. Moreover, if we allow all early adopters into our donor pool (see column 1 of Appendix Table 2), the results are also unchanged.

select an alternate donor pool that includes states that had never adopted a SIPO or had adopted a SIPO but had 4 or fewer days of post-treatment data, meaning that likely at least half of all individuals infected post-SIPO had not yet reached the median incubation period (Lauer et al. 2020). However, this restriction to the donor pool has its own limitation: only 10 states had not adopted SIPOs by April 9 (Arkansas, Iowa, Kentucky, Massachusetts, Nebraska, North Dakota, Oklahoma, South Dakota, Utah, and Wyoming), and just 2 were late adopters that fit this selection criteria (Missouri and South Carolina).[11] Many of these non-adopting and late-adopting states do not share urbanicity, population density, or other policy-related characteristics of California making them potentially bad donors to the synthetic control group.

Thus, selecting the eligible donor states for the analyses to follow has an inherent tradeoff. We can select from a broader set of donor states that allow for a better synthetic control match to California on observables, but partially contaminates our control group with treated days biasing the estimated policy effect towards zero, or, we can select from a more limited set of donor states that is uncontaminated by treatment but that may be poorly matched to California on observables leading to a synthetic control group that is potentially a poor counterfactual for California. We will present results under both choices. The former approach yields policy effects that suggest California's SIPO was effective at slowing the spread of COVID-19 (and is presented in Tables 1 and 4); the latter approach also yields policy effects that suggest California's SIPO was effective (and is presented in columns 2 and 3 of Appendix Table 2), with results that are larger in magnitude (consistent with the prior approach generating a lower bound estimate) but also less precise. It is our opinion that a better synthetic control match that yields a

[11] Among these states, Massachusetts had issued a "stay at home advisory."

downward biased estimate is more reliable than an estimate from a potentially poorly matched control group, a point to which we will return below.

With regard to the choice of observables used to select our synthetic control from among the donor states, we take several approaches. First, an important objective of this research design is to generate common pre-treatment trends in coronavirus cases (or deaths). Our primary strategy to achieve this objective is to generate a synthetic control that closely approximates coronavirus case (and mortality) rates in California in each of seven (7) pre-treatment days (March 12 through March 18). We also experimented with requiring pre-treatment matches up to two weeks (14 days) prior to California's SIPO and our results are unchanged. We estimate the unobserved counterfactual COVID-19 case rate for California on pre-treatment day t by $\sum_j w_j * Case\ Rate_{jt}$, where w_j is the weight assigned to donor state j. The analogous counterfactual death rate is $\sum_j w_j * Death\ Rate_{jt}$. The estimated weights w_j are chosen to minimize the absolute difference between $Case\ Rate_{i=CA,t}$ and $\sum_j w_j * Case\ Rate_{jt}$ and for all pre-treatment days, as well as the absolute difference between $Death\ Rate_{i=CA,t}$ and $\sum_j w_j * Death\ Rate_{jt}$. Then, the per-day treatment effect α_t is estimated as $\alpha_t = Y_{i=CA,t} - \sum_j w_j * Y_{jt}$ for t ∈ r [March 19, April 9], where $Y = [Case\ Rate, Death\ Rate]$. The average treatment effect is then the average over the post-treatment window.

Choosing a counterfactual based only on pre-treatment outcomes has a number of advantages (Hansen et al. 2020). Given a long enough pre-treatment window, matching on covariates and matching on outcomes will produce similar results. Choosing not to match on covariates can eliminate concerns of 'p-hacking' and reduce bias of our estimate (Botosaru and Ferman, 2017). Furthermore, matching on outcomes on pre-treatment days ensures that synthetic CA tracks actual CA not just on the level of the outcome but also on the growth rate of the outcome in the pre-policy period.

However, a limitation of matching all pre-treatment days to construct synthetic California is that there may be other observables that may legitimately and strongly influence the path of an outbreak such as population density, urbanicity, weather, state travel restrictions, or a declaration of major disaster. As shown by Kaul et.al (2018), matching on all periods of pre-treatment outcomes renders all covariates irrelevant in the prediction of the outcome.

Thus, we take alternate approaches to generating a synthetic control that allow for these relevant observables to influence estimation of synthetic weights. First, we generate weights by matching on coronavirus case (or death) rates on three pre-treatment days (March 13, March 15, and March 18) as well as state population density and a state urbanicity index. These latter factors play an important role in the spread of infectious disease across communities due to increased crowding (Florida 2020). New York City, the most densely populated city in the U.S., for example, experienced one of the most dramatic increases in coronavirus outbreaks and has more coronavirus cases per capita than the nation of Italy (Rosenthal 2020).

Second, we generate synthetic weights using March 13, March 15, and March 18 coronavirus case (or death) rates and several state policies designed to affect the outbreak: whether an emergency major disaster declaration was in effect for the state and whether the state had imposed travel restrictions (i.e. guidelines for residents and/or visitors to quarantine themselves for two weeks following arrival from other states).

Third, we consider the role of state COVID-19 testing rates. One reason why we might see changes in cases is because testing resources have changed. 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, states including Delaware, New York, Massachusetts and Texas, began implementing drive-up testing sites, which made access to testing more available (Yancey-Bragg 2020). Despite these improvements in accessibility, many testing delays persisted due to laboratory capacity constraints (Brown and Court 2020). Coronavirus-related deaths are less likely to be affected by this selection into testing. Nevertheless, we take two approaches to explore the issue of testing capacity. For our first approach, we explore if California's SIPO affected testing rates, using synthetic control methods described and the number of tests as the outcome variable. For our second approach, we return to our main analysis of case (and death) rates and generate a synthetic California using March 13, 15 and 18 pre-treatment case (and death) rates as well as the average rate of testing per 100,000 population.

To conduct hypothesis tests, we take two approaches. First, we conduct placebo tests following the method suggested by Abadie et al. (2010). We apply the same synthetic control method described above for each donor state. For donor state *j*, we reclassify the state as a treatment state, and select a donor pool based on all donor states except *j*, and add California to the donor pool. We then use the same matching criteria stated above to generate a synthetic control $Synth_{jt}$ for each donor state *j* as if treatment were assigned March 19.

We compare the pre-treatment and post-treatment mean squared prediction error (MSPE) for each state, calculating the MSPE ratio as follows:

$$MSPE\ ratio_j = \frac{\sum_{t=3/19}^{T}(Y_{jt} - Synth_{jt})^2}{\sum_{t=3/12}^{3/18}(Y_{jt} - Synth_{jt})^2} \qquad (1)$$

The MSPE measures a relative goodness of fit for each state's synthetic control based on estimated coronavirus cases (or deaths). A high MSPE ratio can be interpreted as poor post-treatment fit relative to pre-treatment fit. The ranking of the treated states relative to the placebo states then provides a permutation-based p-value. The p-value relies directly on the number of states in the donor pool. With 43 states in the donor pool, California's MSPE ratio must rank at least 2nd to receive a p-value below .05 and at least 4th to receive a p-value below .1. A p-value of less than .01 is not attainable given the number of donor states.[12]

The p-value generated for the "standard" synthetic control model generates information on post-treatment fit based on the entire post-treatment period following the March 19 California order. However, there are some important reasons why we might want to calculate MSPE over particular post-treatment windows. For example, differences in the California "gap" (the difference between California's coronavirus rate and synthetic California's coronavirus rate) is expected to be much smaller during the incubation period (median of 5.1 days, 97.5th percentile of 11.5 days) following the SIPO relative to the post-incubation period when symptoms would have been present and infectious disease transmission more efficient. Moreover, given that the effects of social distancing may have important multiplier effects over time (Florida 2020), we could expect the "gap" to increase exponentially following treatment. For these reasons, we provide a range of permutation p-values based on several post-treatment windows: (i) the entire post-treatment period, (ii) the post-SIPO period after the median incubation length (March 24 and later), and (iii) the post-SIPO period after which 97.5 percent of those infected on the SIPO implementation date are expected to experience symptoms (March 30 and later).

Second, we conduct statistical inference by estimating wild bootstrap cluster standard errors (Cameron et al. 2008; Cameron and Miller 2015) using difference-in-differences

[12] The null hypothesis utilizing these p-values is that there is no effect in each period, not that the average policy effect is zero. It is possible to have a policy effect with an average of zero in the post-treatment period, but a large MSPE if the effect of the policy changes sign in the post-period. For this reason, it is important to make judgements based on both the MSPE and the general pattern of results. See Powell (2018).

regressions. We draw data from California and donor states that received positive synthetic weights in the construction of synthetic California and estimate a difference-in-differences model of the following form:

$$\ln\left(\textit{Case Rate}_{it}\right) = \beta_0 + \beta_1 \mathrm{SIPO}_{it} + \beta_2 X_{it} + \gamma_s + \tau_t + \mu_{it} \qquad (2)$$

where SIPO_{it} is an indicator for the day that California adopts a shelter-in-place order, X_{it} is a set of state-level, day-varying controls that include indicators for whether the state enacted a statewide non-essential business closure order (that falls short of a shelter-in-place order), whether the state enacted a targeted shelter-in-place order that covers only older individuals over age 65 or those with underlying health conditions, whether the state had enacted travel-related restrictions, whether a major disaster declaration had been issued for the state, the average temperature (in degrees Celsius) at all weather stations in the state, and an indicator for whether any weather station in the state reported measurable precipitation. In addition, we control for state fixed effects (γ_s) and day fixed effects (τ_t), identifying our treatment effect (β_1) via within-state variation in the enactment of a SIPO. We also estimate equation (2) where we replace *Case* $\textit{Rate}_{it}$ with $\textit{Death Rate}_{it}$, but given low counts of deaths during the earlier days of our analysis period, we experiment with count data models such as Poisson and negative binomial models.

We first estimate equation (2) using an unweighted linear regression, giving equal weight to California and each positively synthetically-weighted donor state. Then, we use the synthetic weights (between 0 and 1) generated from the synthetic control model to weight each state and then assign California a weight of 1. In all cases, to conduct statistical inference, we generate standard errors via wild cluster bootstrapping given the small number of clusters (states), which includes a single treatment state (Cameron et al. 2008; Cameron and Miller 2015).

4. Results

Our main findings on the effects of California's statewide SIPO can be found in Figures 4 through 18 and Tables 1 through 6. Discussion of county-specific COVID-19 SIPOs are discussed in Section 4.4 and in Tables 7 and 8.

4.1 "Stay at home" Behavior and California Statewide SIPO

Figure 4 presents trends in the shelter-in-place index for both California and its synthetic control. The index reflects the percent of the population in a given state that stays at home all day relative to a baseline, derived from anonymized cell phone geotagging (SafeGraph, Inc.). We assign weights to the synthetic control based on close matches in the shelter-in-place index for each of the 7 days prior to CA's statewide SIPO.[13] Trends in social distancing are expectedly positive over the entire analysis period as awareness of COVID-19 was proliferating and the benefits of social distancing were emphasized through public health advisories and guidelines. The synthetically-generated counterfactual tracks California nearly identically prior to the SIPO, with trends markedly diverging only after California issued its statewide order on March 19. Estimates of the average daily treatment effect indicate that the percent of individuals remaining at home throughout the day increased by 2.1 percentage-points in California relative to its synthetic control, over the entire post-SIPO period. The effect is larger over the initial post-

[13] As the baseline for the index is the same for all states (week ending February 12, 2020), and the pre-SIPO trends are nearly identical, the treatment effect can be interpreted as the increase in the percent of households in CA who are staying at home relative to its counterfactual in the post-SIPO period.

treatment window up to March 28, indicating a 3.3 percentage-point increase in the average daily rate at which individuals shelter at home in California relative to the synthetic control, and suggestive of a rapid run-up in social distancing. Focusing on this window wherein CA experienced the largest gains in social distancing, the effect is statistically significant with a one-sided permutation-based p-value of 0.023. As more donor states issued their own shelter-in-place orders, notably by the end of March, and gains for California decelerated, trends narrowed somewhat between California and its synthetic control.

These analyses underscore two points. First, they provide some supporting evidence that individuals in California complied with the shelter-in-place order, and that the SIPO effectively and rapidly reduced social mobility in California, an effect which was sustained over the analysis period. Second, as pressure for social distancing intensified, the health effects that we estimate below capture the direct effect of California's SIPO on contagion by forcing certain forms of economic activity to stop as well as the compounding effects of the SIPO accelerating social distancing behavior during the early period of the coronavirus outbreak cycle.

4.2 COVID-19 Confirmed Cases and California Statewide SIPO

Figure 5a shows trends in California's confirmed COVID-19 cumulative cases from March 12, 2020 through April 20, 2020. Case rates rose fairly linearly over the period from March 12 through March 25 from .6 to 8 per 100,000 population before beginning more exponential growth, reaching 85.6 per 100,000 on April 20, 2020.

Our first synthetic control assigns weights based on close matches in pre-SIPO case rates on each of the 7 pre-treatment days. We find that a total of 10 states contributed approximately two-thirds of the weight for the estimated counterfactual. These include Colorado, the District of

Columbia, Hawaii, Maine, Massachusetts, Michigan, Minnesota, New Mexico, Rhode Island and South Dakota (Figure 5b).[14] This estimated synthetic control serves as our counterfactual for coronavirus case trends that would have unfolded in California in the absence of the SIPO enactment. Figure 5a shows that COVID-19 case rate trends in California and synthetic California are nearly identical in the pre-March 19 period. During the first three (3) days following treatment, which capture the first half of the coronavirus incubation period, coronavirus case rates remain quite similar in California and the synthetic control state. However, beginning on March 23 and accelerating after March 25, the rate of growth in California's coronavirus cases was substantially lower in California relative to the synthetic control. By the final day of case data in our analysis (April 20), we find that there were 125.5 fewer coronavirus cases per 100,000 population, which translates to 49,636 fewer total cases on that day. This pattern of findings suggests that the public health benefits of the SIPO grew over the near-month long period of analysis. These public health benefits also capture any potential compounding effects due to California responding early during the initial phase of its outbreak cycle.[15]

In column (1) of Table 1, we show estimates of the average daily treatment effect for the full post-SIPO period from March 19 through April 20 (Panel I), for the post-treatment period beginning March 23, which accounts for the median coronavirus incubation period (Panel II), and for the post-SIPO period beginning March 30, the 97th percentile of the coronavirus incubation period (Panel III). For the full post-treatment period, we estimate that the enactment

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[14] The highest synthetic weights were assigned to Colorado (11%), the District of Columbia (3%), Maine (10%), Massachusetts (15%), and South Dakota (18%).

[15] If we employ the synthetic weights from Model 1 (Table 1) to compute a weighted average date of SIPO enactment among the states in the control group and assign never adopters a pseudo-treatment date that is one day after the end of the analysis period, then, using this measure, California issued its SIPO on average 13 days prior to synthetic California.

of the SIPO is associated with a 42.02 decline in average coronavirus cases per 100,000 population. Over the near month-long window, this suggests approximately 49,636 COVID-19 cases averted.[16]

The daily decline in coronavirus cases is not constant over the post-treatment window. The estimated public health benefits accelerate in the days following enactment, consistent with an exponential growth in contagion that was averted from the SIPO's enactment. Following March 22, the enactment of the SIPO led to a 47.7 decline in average coronavirus cases per 100,000 population while in the post-March 30 period, the average cumulative case reduction that we attribute to California's SIPO is 61.0 per 100,000 population. Together, this evidence is consistent with the hypothesis that the public health benefits of California's SIPO grew exponentially in the short-run.

To conduct statistical inference of the above estimates, we turn to permutation-based p-value calculations. In Figure 5c, we show results from our placebo tests, which give rise to the rank-based p-values we generate. In each case, the permutation-based p-value was .045 using the standard ranking generated by the pre-post MSPE ratio, and .045 using a one-tailed pre-post MSPE ratio test.

An important concern in synthetic control analysis is how robust findings are to the choice of observable controls and donor states. Figure 6a shows results from a synthetic control approach where we only assure pre-treatment matches on COVID-19 cases on three days (March 13, March 15, and March 18), but also augment our matching strategy by assuring similarity on the share of the state population residing in urban areas. According to the 2010 Census, 95.0

[16] To take a more conservative approach, we also consider an alternate strategy where we force coronavirus cases during the period from March 19 through March 23 to be comparable to the donor states. This imposes a null effect of the SIPO on cases due to lagged effect from exposure to symptoms during the incubation period. This exercise, shown in Appendix Figure 4, yields similar results as our main model.

percent of the population lived in urbanized areas or urban clusters. In Appendix Table 3, we compare urbanicity rates in California (column 1) with all other states (column 2), and synthetic California (column 3). We find that urbanicity rates are most similar to California with the synthetic counterfactual.

Despite generating a very different set of positively weighted donor states from the approach undertaken in Figure 5a, the estimated treatment effect is quite similar, as is the pre-treatment match.[17] There is a tight pre-treatment fit, with an exponential divergence following the post-SIPO initial virus incubation period. In column (2) of Table 1, we show that over the full post-treatment period, the California SIPO led to a 56.3 per 100,000 population decline in average cumulative coronavirus cases. Again, the effect sizes were larger in later days of the post-treatment period (Panels II and III), consistent with exponential growth in public health benefits to those in California. The permutation-based p-value from placebo tests (Figure 6c) is .023 in all panels.

Given that urbanicity rates may not fully capture the degree of crowding, in Figures 7a through 7c, we show results from a synthetic control model where we match not only on urbanicity, but also population density, increasing the likelihood that we more heavily weight those donor states with higher risk of coronavirus contagion.[18] Our findings, shown in Figures 7a-7c and in column (3) of Table 1, are quite similar to those in column (2) of Table 1.

To ensure that coronavirus testing is not biasing estimates of the effect of California's SIPO on confirmed cases, we next select weights for donor states by also matching on the

[17] In Appendix Table 4, we show synthetic control estimates where we limit the donor states to the continental United States, thus eliminating Alaska and Hawaii as potential donors. The pattern of results is qualitatively similar to that shown in Table 2.
[18] Appendix Table 3 shows the quality of the synthetic control on these observables.

average rate of testing over the sample period.[19] The results in Appendix Figures 2a through 2c provide some support for the hypothesis that testing for the coronavirus may have increased in the short-term following the SIPO, suggesting that estimated case reductions may be biased toward zero. Though, after about two weeks following CA's SIPO, testing rates in the control group increased more rapidly relative to CA. After controlling for average coronavirus testing rates, we find that the California SIPO led to an average reduction of 61.6 COVID-19 cases per 100,000 population. By April 20, we estimate 68,157 COVID-19 cases averted (Figures 8a-8c and column 4 of Table 1).

In column (5), we explore whether our estimated treatment effect is sensitive to the addition of COVID-19-related policy controls, including major disaster declarations and state travel restrictions (see Appendix Table 3). The pattern of results shown in Figures 9a through 9c are quite similar to those shown in the previous figures. We find that the California SIPO led to an average 59.4 case per 100,000 population reduction in COVID-19 cases. By April 20, the cumulative number of coronavirus cases averted was approximately 66,020 (based on column 5 of Table 1).

One important question about our prior analyses is whether we are identifying the effect of a SIPO or just voluntary social distancing that is correlated with the adoption of a SIPO and with coronavirus cases. In column (6) of Table 1, we match on pre-treatment growth in rates of staying-at-home using SafeGraph data as well as three days of pre-treatment coronavirus cases. Here, we estimate that over the near-month long pretreatment period, California's SIPO was associated with a nearly 87,000 decline in the total number of COVID-19 cases. Figures 10a-10c show these results.

[19] Appendix Table 3 shows means of testing rates for California and its synthetic control.

Could our donor states be too different from synthetic California in experiencing community spread of the coronavirus? Different states experienced coronavirus outbreak at different times. In the pre-treatment period, California had experienced nearly 252 cases of COVID-19 on March 12, which suggests that outbreak and community spread was well underway. To ensure that the donor pool for synthetic California had also experienced community spread, in Table 2, we limit our donor pool to states that had experienced at least 10 (column 1), 50 (column 2), or 100 cases (column 3) of coronavirus. The results in Table 2 and Figure 11 continue to show strong evidence that California's SIPO was associated with a reduction in COVID-19 cases.

It is important to recall that each of the above estimates is based on a synthetic control from a set of donor states that are partially treated in the latter part of the post-period, and as such are a lower bound for the true effect of the policy.[20] In columns (2) and (3) of Appendix Table 2, we examine the sensitivity of estimated policy impacts to the use of never-adopting or later-adopting (after April 5) states as controls. We find that California's statewide SIPO reduced average cumulative case rates by about 66 cases per 100,000 relative to synthetic California. These results are larger in magnitude, but also less precise than the estimates when we allow partially treated states in the control group.

Appendix Figure 7 presents the corresponding trends in cumulative cases for California and synthetic California. While these results are validating, we note here the qualification that the set of donor states that receive positive weights among non-adopters include Massachusetts

[20] In Appendix Figures 5 and 6, we trim the post-treatment window in order to limit the effects of later SIPOs enacted by states within the synthetic control. Specifically, Appendix Figure 5 trims the post-treatment period to March 28, which is 5 days (median incubation period) after the first treatment date for any donor state, ensuring that the trend in cases exhibited by synthetic CA is not due to a SIPO enacted within the control group. Appendix Figure 6 slightly extends the post-treatment period to April 3, ensuring that the window ends before the median incubation period plus lag to ARDS (13 days). Both figures show consistent evidence that the statewide SIPO in CA flattened its outbreak trajectory and reduced the average daily COVID-19 cases.

(38 percent), Oklahoma (22.4 percent), Utah (22.3 percent), North Dakota (14 percent), and Wyoming (3.2 percent). Appendix Table 5 shows that the synthetic California estimated from never adopters (columns 2 and 3) and never or late adopters (columns 4 and 5) differ on population density and urbanicity. Given the important role of social interactions in the spread of the coronavirus, this makes it possible that the synthetic California generated from a much narrow set of never (or later) adopting donor states were on a different longer-run coronavirus contagion trend, and thus may serve as a poor counterfactual for California.[21]

Table 3 presents difference-in-differences estimates of the effect of California's SIPO on the natural log of confirmed COVID-19 cases. In each case, the sample is comprised of California and each donor state that received a positive weight in the synthetic control exercise described by each column, which follows the set of tests from Table 3. Panel I shows estimates from unweighted regressions, while Panel II uses synthetic weights (which sum to 1) for the donor states and a weight of 1.0 for California. All models include the full set of controls described below equation (2) above. Standard errors are generated via wild cluster (state) bootstrap.

Our findings provide consistent evidence that the California SIPO had substantial negative effects on coronavirus cases. Unweighted estimates in Panel I show that the enactment of California's SIPO was associated with a 50.3 to 59.0 percent decline in the coronavirus rate. When we weight using synthetic weights (Panel II), the effect sizes range from approximately 35.5 to 54.1 percent declines.[22]

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[21] This may also help explain why the estimated effects for deaths in Panel II of Appendix Table 2 are weak and do not attain statistical significance at conventional levels. The longer lag from infection to incubation to ARDS limits the quality of the synthetic control match when drawing from the smaller pool of never or late adopters.
[22] Given that the outcome is the log of the caseload, the percent decline for model 1 is $[e^{-0.609} - 1]*100 = 45.6\%$.

In Panel III of Table 3, we focus on regressions weighted by synthetic weights and decompose the average treatment effect based on the approximate interquartile range of the incubation window following enactment of the SIPO. Consistent with the synthetic control estimates, we find that the effectiveness of the SIPO grows larger following the virus's incubation period and the period from time until first symptom until respiratory failure.

Together, the findings in Tables 1 through 3 provide compelling evidence that California's first-in-the-nation SIPO generated important public health benefits in preventing the spread of the coronavirus during the first three weeks of enactment.[23] Next, we explore whether these case declines generated improvements in mortality rates.

4.3 COVID-19 Deaths and California Statewide SIPO

In Figures 12a through 12c, we show estimates of the effect of California's SIPO on coronavirus-related mortality. Figure 12a shows the exponential rise in cumulative COVID-19-related deaths in California, from 0.01 per 100,000 population (4 deaths) on March 12 to 3.09 per 100,000 population (1,223 deaths) on April 20. When we generate a synthetic control using all pre-treatment days to generate matches on COVID-related mortality rates, we find strong evidence of a pre-March 19 common trend for California and synthetic California. On March 25, 6 days following enactment of the SIPO, we find that the rate of increase in mortality begins falling in California as compared to the estimated counterfactual, with a gap that widens

[23] In Appendix Figures 3a through 3c, we show synthetic control results when we use daily case rates rather than cumulative case rates. This isolates a different local average treatment effect; that is, the effect of a SIPO on the rate of change in the change in cumulative coronavirus cases. Furthermore, this exercise explicitly matches on the daily growth in COVID-19 cases in all of the pre-SIPO periods. By doing so, we are also implicitly matching on the second derivative of the cumulative case rate function, which is the growth in the daily change or the acceleration in the growth in daily case rates. Daily case rate data are more noisy, but the results continue to provide evidence that California's SIPO reduced coronavirus-related mortality.

exponentially over time, getting particularly large nearly two weeks after the policy's adoption on March 31, 2020.

This longer lagged effect on mortality relative to cases is to be expected given the incubation period from exposure to symptoms and time from first symptoms to acute respiratory distress syndrome (ARDS), the latter of which may take up to 8 days (Wang et al. 2020). Moreover, a more conservative synthetic control approach, shown in Appendix Figures 8a through 8c, which requires pre-treatment mortality rate matches for every period through the sum of the median incubation length (5.1 days) and the median symptoms-until-near-death (8.0 days), shows a sharp relative decline in coronavirus-related mortality rates in California.[24] Finally, we note that there are channels through which mortality may be affected by SIPOs that are not directly affected by exposure to contagious infected patients. SIPOs may affect the likelihood that previously infected patients seek medical care due to beliefs about contagion at medical facilities. SIPOs may also impact the availability of resources for medical care, including testing, as public resources are used to enforce SIPOs.

Our estimates in column (1) of Table 4 show that California's SIPO led to an average decline in the coronavirus death rate of approximately 1.4 per 100,000. By April 20, there were 763 fewer COVID-19 deaths. Combined with the estimated case effect shown in column (1) of Table 4, our estimated mortality effect implies a coronavirus-related mortality rate of 3.3 percent, somewhat high, but within the range of mortality estimates suggested by the WHO and CDC (World Health Organization 2020f; Wilson et al. 2020). Of course, there are a number of caveats to this back-of-the-envelope assessment to judge the credibility of our estimates. First, deaths

[24] Because death rates during the early phase of the outbreak were low for all states, and 0 for a few states during the first few days, we present alternate synthetic control estimates for deaths by matching on COVID-19 cases on all pre-treatment days (see Appendix Figure 9). Estimated effects for mortality rates are not sensitive to matching on case rates, and continue to indicate a marked reduction in deaths in CA relative to the control group.

occur with a lag with respect to confirmed cases. Second, during the earlier stages of the outbreak, there is evidence that state medical resource constraints permitted testing of only those with more severe symptoms and a higher probability of succumbing to their illness (Baker and Fink 2020). Third, this implied mortality rate is based on the margin of cases averted due to the SIPO, which may be different than the average infected case.[25]

While our estimated mortality decline is substantial in magnitude, permutation-based p-values are insufficiently small to conclude definitively that there is a death decline due to California's SIPO. As expected, the size of the death reduction induced by the state SIPO grows much larger when the incubation period and time from symptoms until possible death are excluded from the analysis. We estimate effect sizes that range from –1.59 to (Table 4, column 1, Panel II) to –2.05 (Table 4, column 1, Panel III) per 100,000 population per day.

The remaining columns of Table 4 show the estimated effect of California's SIPO when using the same observables to generate the weights for synthetic California described in columns (2) through (6) of Table 1.[26] Figures 13 through 17 show the corresponding synthetic control graphs. Across specifications, we find evidence that the California SIPO is negatively related to the coronavirus mortality rate, though the magnitude of the effect is somewhat smaller after controlling for observables related to public policies in testing. However, the estimated treatment effect grows later in the treatment window and is largest following March 30, when we expect lagged effects on mortality due to reaching the sum of the median incubation period and median time until ARDS. Somewhat smaller mortality declines are observed in specifications that also match on average testing rates.

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[25] In other words, the implied mortality rate is based on (Δ Death Rate / Δ Case Rate) and may be different than the average mortality rate (Total Death Rate / Total Case Rate).

[26] These estimates imply a marginal coronavirus-related mortality rate of 0.8% to 2.5%.

In Table 5 and in Figure 18, we examine whether the estimated mortality effects we observe are sensitive to requiring donor states to have experienced community spread. The findings suggest that we obtain comparable estimated lives saved as those reported in Table 4. Specifically, we estimate that the adoption of a SIPO is associated with 763 to 1,661 fewer deaths, with a median estimate around 1,500 lives saved.

Finally, in Table 6, we present difference-in-differences estimates of the effect of California's SIPO on COVID-19-related mortality. All models are weighted using the synthetic weights generated in the four main models we have considered. Panel I shows our findings on the average treatment effect in the post-treatment period, while Panel II decomposes the treatment effect into the early period when death effects should be relatively small (time from incubation until ARDS) and the latter period accounting for this lag. We find evidence that the mortality declines from the implementation of the SIPO are generally larger in the period following March 30, as expected. However, uniformly, estimates are fairly imprecise, in part owed to low COVID-19 mortality rates in the state. During this period, we find the SIPOs reduce COVID-related mortality by between 12.5 to 17.5 percent per day.

Given low counts of deaths, in Panels III and IV of Table 6, we present estimates from Poisson models. We find much stronger evidence of negative impacts of California's SIPO on mortality. In the post-incubation-until-ARDS period (Panel IV), we find consistent evidence that the SIPO was associated with a 46.2 to 73.7 percent decline in deaths.[27]

[27] Given the possibility of overdispersion in deaths, we also estimated these count models via negative binomial regression. While computationally more intensive, we find estimated SIPO effects that are qualitatively similar. For example, in column (1) of Panel III, we find that that the SIPO was associated with a 51 percent decline in deaths. This compares to an identical decline using a negative binomial model.

Taken together, the results from Tables 4 through 6 provide strong evidence that California's SIPO generated substantial short-run public health benefits via reduced coronavirus-related mortality.

4.4 California County-Level Analysis

Prior to the adoption of California's statewide SIPO, 12 counties and the cities of Los Angeles and Berkeley adopted local SIPOs. Appendix Table 6 lists these jurisdictions and their dates of enactment. If early SIPO adoption in the midst of an exponential expanding epidemic, particularly in high population density localities, can generate large public health benefits, these early adopting jurisdictions may have seen earlier and more pronounced declines in COVID-19 cases.

In Table 7, we provide descriptive evidence that this may be the case. In columns (1) and (2), we provide evidence on pre-treatment county-level coronavirus case and death rates. We find that coronavirus rates were much higher in early adopting SIPO counties (ESIPOs). However, we see that growth in coronavirus cases was substantially lower in ESIPO counties as compared to those who were bound by the statewide policy. Between March 5 and April 20, the coronavirus case rate increases by over 42 times in ESIPO counties, but well over 316 times in those who adopted SIPOs later. Due to many low population counties with zero deaths for much of the sample period it is difficult to draw reliable inference with regards to county-level SIPOs and mortality.

Synthetic control estimates in Table 8 on ESIPO counties, which match on pre-treatment coronavirus case rates in ESIPO and non-ESIPO counties do not, in the main, suggest a significant divergence in trends in these outcomes, either in the earlier period following enactment or over time. Only for the county of Santa Cruz is there some evidence that cases fell more than in its synthetic counterfactual, generated from other California counties. However, we note an important caveat with our county-specific findings. Appendix Figure 10 shows that many California counties did not have particularly strong pre-treatment matches on coronavirus cases. Many ESIPO counties were already trending upward in coronavirus cases prior to the adoption of an ESIPO relative to other counties. Furthermore, the cross-county analyses are challenged by the close proximity of the SIPOs among the early adopting counties with the statewide order, with all of these orders occurring within a span less than the median incubation period of the coronavirus, making it difficult to identify potentially small differences in the post-treatment trends. Thus, we are hesitant to draw any strong conclusions about the effectiveness of CA's early adopters using within-state comparison counties as donors.[28]

5. Conclusions

On March 19, 2020, California Governor Gavin Newsom implemented the nation's most radical response to a worldwide coronavirus outbreak: implementing a statewide shelter-in-place order that required citizens to remain inside their dwellings for all but activities deemed "essential," such as grocery shopping, pharmaceutical pick-up, caring for sick relatives and friends, or employment deemed essential. This policy was designed to slow the spread of the coronavirus by enforcing social distancing through legal force and social pressure. The high level of urbanicity in California, combined with policy adoption during a period of slow coronavirus cases, make this state a unique case study of early precautionary policies in a high-risk environment.

[28] This pattern of findings did not change when we attempted to generate synthetic county controls based on within-California county-specific matches on urbanicity and population density.

This study is the first to rigorously examine the short-run impact of California's SIPO on the rate of confirmed COVID-19 infections and COVID-19-related mortality. Using a synthetic control approach, we estimate that in the near-month following the order, the state SIPO reduced the number of COVID-19 cases by 125.5 to 219.7 per 100,000 population. In addition, our synthetic control estimates suggest that the California SIPO averted up to 1,661 COVID-19-related deaths. Thus, our estimates suggest a mortality rate of about one to three percent at the margin of averted cases. We note that these benefits represent the effects of having a SIPO in place as well as the effects of doing so early in the outbreak cycle. Notably, the synthetic control issued a SIPO later in the outbreak cycle, about 13 days on average following California. Hence, the treatment effects for CA also capture the potential benefits of an early response.

These findings are robust to the choice of observables with which we weight potential donor states. Moreover, lagged case and mortality effects are consistent with the median incubation period of COVID-19 as well as estimates of time from first symptoms until acute respiratory distress syndrome. We find little evidence that changes in testing for coronavirus leads to substantial bias in our estimates. Finally, turning to county-level data, we find little evidence that counties that adopted SIPOs prior to California's statewide SIPO law saw earlier and more pronounced declines in coronavirus cases than their later adopting California counterparts, though this may be due to the relatively short span of time (4 days) between when the early adopters enacted the shelter-in-place order and the statewide order.

The statewide results we present show substantial short-run public health benefits of California's SIPO. But we also note that there were substantial economic costs of this intervention. In addition to substantial utility losses caused by social distancing from non-household members (Hamermesh 2020), the SIPO was accompanied by substantial job loss.

Unemployment insurance claims in California rose by 2.83 million in the four weeks during which we studied mortality reductions (U.S. Department of Labor 2020). If we net out the average increase in the weekly jobless claim rate of our preferred "synthetic California" for COVID-19 cases (column 1 of Table 1) as a proxy for how weekly job loss would have evolved in California, estimates of job loss are nearly 75 percent smaller, a finding consistent with new work by Baek et al. 2020). Back-of-the-envelope calculations suggest, at the lower bound, over 400 jobs were lost per COVID-19 death averted.[29,30]

Some of the aforementioned job losses may be short-term to the extent that they are due to a temporary decrease in aggregate demand and consumer spending which may rebound once the SIPO is lifted and the risk of infection weakened. Further, government spending packages such as the Coronavirus Aid, Relief, and Economic Security (CARES) Act, which is designed to infuse firms with public funds to remain open until SIPOs were lifted may blunt the total job loss impact (although the long run impact of the bill, which cost over $2 trillion, on future public and private finances is difficult to predict). Finally, we note that the vast majority of deaths averted from coronavirus are among the elderly and those with underlying health conditions (Wu and McGoogan 2020; Verity et al. 2020; CDC Covid-19 Response Team 2020). Thus, the SIPO represents a substantial intergenerational redistribution of resources toward the older and infirmed.

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[29] We note, however, that the dynamics of job loss following SIPOs may be quite different from coronavirus cases. For example, if job losses following the implementation of a SIPO occurs sooner than coronavirus cases or deaths are averted, synthetic California is likely to be more contaminated from donor states than coronavirus cases averted (due to the lack of an incubation or time from symptoms-until-ARDS lag). If this is the case, then the jobs per case averted (or life saved) reported above will be understated.

[30] Appendix Figure 11 shows a synthetic control estimate using weekly jobless claims data from the U.S. Department of Labor through April 11. The outcome represents the rate of weekly jobless claims relative to covered jobs in the state. We generate synthetic California using the same weights used for our coronavirus case synthetic control using pre-treatment COVID-19 case matches.

There are several dimensions in which future work will be important. First, in the absence of a vaccine or effective treatment for COVID-19 in the short term, the chief public health rationale for temporary shutdown orders is to reduce serious COVID-19-related illnesses and deaths due to short-run medical capacity constraints (Greenstone and Nigam 2020). If some of the deaths or illnesses are postponed to the future when the SIPO is lifted, the intervention's net health benefits will be smaller. Second, California was uniquely positioned to reap important short-run health benefits from its SIPO given the state's high urbanicity rate and the enactment of the SIPO during a period of very low COVID-19 case growth. Other jurisdictions with less crowding, less medical preparedness, or higher rates of pre-SIPO COVID-19 case growth may have very different experiences.

6. References

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

Abouk, Rahi, and Babk Heydari. 2020. "The Immediate Effect of COVID-19 Policies on Social Distancing Behavior in the United States." Available at SSRN: https://ssrn.com/abstract=3571421

Allday, Erin. 2020. "Bay Area Orders 'Shelter in Place,' Only Essential Businesses Open in 6 Counties." *San Francisco Chronicle*, March 16. Available at: https://www.sfchronicle.com/local-politics/article/Bay-Area-must-shelter-in-place-Only-15135014.php

Arnold, Chris. 2020. "U.S. Coronavirus Testing Gets A Potential Breakthrough." *NPR*, March 13. Available at https://www.npr.org/2020/03/13/815522836/u-s-coronavirus-testing-gets-a-breakthrough

Arnold, Chris. 2020. "America Closed; Thousands of Stores, Resorts, Theaters Shut Down." *NPR*, March 16. Available at: https://www.npr.org/2020/03/16/816398498/america-closed-thousands-of-stores-resorts-theaters-shut-down

Australian Government Department of Health. 2020. "Social Distancing for Coronavirus (COVID-19)." Available at: https://www.health.gov.au/news/health-alerts/novel-coronavirus-2019-ncov-health-alert/how-to-protect-yourself-and-others-from-coronavirus-covid-19/social-distancing-for-coronavirus-covid-19

Baek, ChaeWon, Peter McCrory, Todd Messer, and Preston Mui. 2020. "Unemployment Effects of Stay-at-Home Orders: Evidence from High Frequency Claims Data," UC Berkeley Working Paper.

Baker, Mike and Sheri Fink. 2020. "At the Top of the Covid-19 Curve, How Do Hospitals Decide Who Gets Treatment?" *The New York Times*, March 31. Available at: https://www.nytimes.com/2020/03/31/us/coronavirus-covid-triage-rationing-ventilators.html

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan. 2004. How much should we trust differences-in-differences estimates?. *The Quarterly Journal of Economics 119*(1): 249-275.

Brown, Kristen V. & Emma Court. 2020. "U.S. Labs Face Crisis After Crisis Despite Improvements in Testing." *Bloomberg*, April 7, 2020. Available at: https://www.bloomberg.com/news/articles/2020-04-07/coronavirus-testing-accuracy-and-availability-shortages-remain

Botosaru, Irene., & Bruno Ferman 2019. "On the Role of Covariates in the Synthetic Control Method." *The Econometrics Journal* 22(2): 117-130.

California, State of. 2020. “Executive Order N-33-20.” Available at: https://www.gov.ca.gov/wp-content/uploads/2020/03/3.19.20-attested-EO-N-33-20-COVID-19-HEALTH-ORDER.pdf

California Department of Parks and Recreation. 2020 “COVID-19 Closures” Available at: https://www.parks.ca.gov/?page_id=30355

Cascella, Marco, Michael Rajnik, Arturo Cuomo, Scott C. Dulebohn, Raffaela Di Napoli. 2020. “Features, Evaluation and Treatment Coronavirus (COVID-19).” *NCBI*, March 20. Available at: https://www.ncbi.nlm.nih.gov/books/NBK554776/

Cameron, A. Colin, and Douglas L. Miller. 2015. "A practitioner’s guide to cluster-robust inference." *Journal of Human Resources* 50(2): 317-372.

Cameron, A. Colin, Jonah B. Gelbach, and Douglas L. Miller. 2008. “Bootstrap-based Improvements for Inference with Clustered Errors.” *Review of Economics and Statistics* 90: 414–427.

Centers for Disease Control and Prevention. 2020a. “Coronavirus Disease 2019 (COVID-19): How It Spreads.” Available at: https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/how-covid-spreads.html?CDC_AA_refVal=https%3A%2F%2Fwww.cdc.gov%2Fcoronavirus%2F2019-ncov%2Fprepare%2Ftransmission.html

Centers for Disease Control and Prevention. 2020b. “Social Distancing, Quarantine, and Isolation” Available at: https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/social-distancing.html

Centers for Disease Control and Prevention. 2020c. “Coronavirus Disease 2019 (COVID-19): Symptoms.” Available at: https://www.cdc.gov/coronavirus/2019-ncov/symptoms-testing/symptoms.html

Centers for Disease Control and Prevention COVID-19 Response Team. 2020. “Morbidity and Mortality Weekly Report: Preliminary Estimates of the Prevalence of Selected Underlying Health Conditions Among Patients with Coronavirus Disease 2019 – United States, February 12-March 28, 2020.” Available at: https://www.cdc.gov/mmwr/volumes/69/wr/mm6913e2.htm

Cohen, Jon. 2020. “’I’m Going to Keep Pushing.’ Anthony Fauci Tries to Make White House Listen to Facts of the Pandemic.” *Science Magazine*, March 22. Available at: https://www.sciencemag.org/news/2020/03/i-m-going-keep-pushing-anthony-fauci-tries-make-white-house-listen-facts-pandemic

Desiderio, Andrew and Marianne Levine. 2020. "Congress livid over lags in coronavirus testing." *Politico*, March 12. Available at: https://www.politico.com/news/2020/03/12/coronavirus-testing-127016

Ferman, Bruno, Cristine Pinto, and Vitor Possebom. 2017. "Cherry Picking with Synthetic Controls."

Fineberg, H. V. National Research Council. 2020. *Rapid Expert Consultation on the Possibility of Bioaerosol Spread of SARS-CoV-2 for the COVID-19 Pandemic (April 1, 2020)*. Washington, DC: The National Academies Press. https://doi.org/10.17226/25769.

Florida, Richard. 2020. "The Geography of Coronavirus." Available at: https://www.citylab.com/equity/2020/04/coronavirus-spread-map-city-urban-density-suburbs-rural-data/609394/

Food and Drug Administration. 2020. "Coronavirus (COVID-19) Update: FDA Continues to Accelerate Development of Novel Therapies for COVID-19." March 31. Available at: https://www.fda.gov/news-events/press-announcements/coronavirus-covid-19-update-fda-continues-accelerate-development-novel-therapies-covid-19

Fry, Hannah. "As Coronavirus Spreads, Los Angeles County Scores an A in Social Distancing; Other Counties Lag." *Los Angeles Times*, March 31. Available at: https://www.latimes.com/california/story/2020-03-31/lcoronavirus-los-angeles-scores-an-a-in-social-distancing-according-to-a-gps-tracking-project

Greenstone, Michael, and Vishan Nigam. 2020. "Does Social Distancing Matter?" *Becker Friedman Institute for Economics Working Paper*, 2020-26. Available at SSRN: https://ssrn.com/abstract=3561244

Hamermesh, Daniel. 2020. "Lockdowns, Loneliness and Life Satisfaction." *National Bureau of Economic Research* Working Paper.

Hansen, B., Miller, K. and Weber, C., 2020. Early evidence on recreational marijuana legalization and traffic fatalities. *Economic inquiry*, 58(2), pp.547-568.

Hicks, Nolan and Julia Marsh. 2020. "Coronavirus in NY: City Has Fewer Than 400 Free Intensive Care Beds." *New York Post*, March 31. Available at: https://nypost.com/2020/03/31/coronavirus-in-ny-nyc-has-fewer-than-400-free-hospital-beds/

House Oversight and Reform Committee. 2020. "Hearing on Coronavirus Response, Day 1." Available at: https://www.c-span.org/video/?470224-1/dr-fauci-warns-congress-coronavirus-outbreak-worse

James, Chris. 2020. "ER Doctor in New York Details Dire Supply Shortages From the Front Lines of the Coronavirus Fight." *CNN*, April 2. Available at: https://www.cnn.com/2020/03/31/us/coronavirus-medical-shortages-us/index.html

Kaste, Martin. 2020. "U.S. Hospitals Prepare for a COVID-19 Wave." *National Public Radio*, March 6. Available at: https://www.npr.org/2020/03/06/812967454/u-s-hospitals-prepare-for-a-covid-19-wave

Kaul, Ashok, Stefan Klößner, Gregor Pfeifer, and Manuel Schieler. 2015. "Synthetic Control Methods: Never Use All Pre-Intervention Outcomes Together with Covariates." Working Paper, Saarland University, Saarbrucken, Saarland, Germany

Kopetman, R. 2020. "Southern Californians who fail to heed coronavirus warnings run into new restrictions, especially at the beach" The Orange County Register. Available at: https://www.ocregister.com/2020/03/22/southern-californians-who-fail-to-heed-coronavirus-warnings-hit-new-restrictions-especially-at-the-beach/

Lauer, Stephen A., Kyra H. Grantz, Qifang Bi, Forrest K. Jones, Qulu Zheng, Hannah R. Meredith, Andrew S. Azman, Nicholas G. Reich, and Justin Lessler. "The Incubation Period of Coronavirus Disease 2019 (COVID-19) from Publicly Reported Confirmed Cases: Estimation and Application." *Annals of Internal Medicine* (2020).

Li, Peng, Ji-Bo Fu, Ke-Feng Li, Yan Chen, Hong-Ling Wang, Lei-Jie Liu, Jie-Nan Liu, Yong-Li Zhang, She-Lan Liu, An Tang, Zhen-Dong Tong, and Jian-Bo Yan. 2020. "Transmission of COVID-19 In The Terminal Stage of Incubation Period: A Familial Cluster." *International Journal of Infectious Diseases*, March 17. Available at: https://www.ijidonline.com/article/S1201-9712(20)30146-6/fulltext

Li, Ruiyun, Sen Pei, Bin Chen, Yimeng Song, Tao Zhang, Wan Yang, Jeffery Shaman. 2020. "Substantial Undocumented Infection Facilities The Rapid Dissemination of Novel Coronavirus (SARS-CoV2)." *Science*, March 16. Available at: https://science.sciencemag.org/content/early/2020/03/24/science.abb3221/tab-pdf

Mandavilli, Apoorva. 2020. "Infected but Feeling Fine: The Unwitting Coronavirus Spreaders." *The New York Times*, March 31. Available at: https://www.nytimes.com/2020/03/31/health/coronavirus-asymptomatic-transmission.html

Marquez, Miguel and Sonia Moghe. 2020. "Inside a Brooklyn Hospital that is Overwhelmed with COVID-19 Patients and Deaths." *CNN*, March 31. https://www.cnn.com/2020/03/30/us/brooklyn-hospital-coronavirus-patients-deaths/index.html

Martineau, Paris. 2020. "What's a 'Shelter In Place' Order, and Who's Affected?" *Wired*, March 20. Available at: https://www.wired.com/story/whats-shelter-place-order-whos-affected/

Meredith, S. "Flattening the coronavirus curve: What this means and why it matters." CNBC News. Available at: https://www.cnbc.com/2020/03/19/coronavirus-what-does-flattening-the-curve-mean-and-why-it-matters.html

Mervosh, Sarah, Denise Lu, and Vanessa Swales. "See Which States and Cities Have Told Residents to Stay at Home." *The New York Times*, April 7. Available at: https://www.nytimes.com/interactive/2020/us/coronavirus-stay-at-home-order.html

Ochmann, Sophie and Max Roser. 2020. "Polio." Available at: https://ourworldindata.org/polio

Petras, George and Janet Loehrke. 2020. "PPE: Types of Personal Protective Equipment Used to Combat COVID-19." *USA Today*, March 31. Available at: https://www.usatoday.com/in-depth/news/2020/03/31/coronavirus-protection-what-health-care-workers-need-stay-safe/2917179001/

Powell, D., 2018. Imperfect Synthetic Controls: Did the Massachusetts Health Care Reform Save Lives?. Available at SSRN 3192710.

Public Health England. 2020. "Guidance on Social Distancing for Everyone in the U.K." Available at: https://www.gov.uk/government/publications/covid-19-guidance-on-social-distancing-and-for-vulnerable-people/guidance-on-social-distancing-for-everyone-in-the-uk-and-protecting-older-people-and-vulnerable-adults

Public Health Agency of Canada. 2020. "Community-Based Measures to Mitigate the Spread of Coronavirus Disease (COVID-19) in Canada." Available at: https://www.canada.ca/en/public-health/services/diseases/2019-novel-coronavirus-infection/health-professionals/public-health-measures-mitigate-covid-19.html

Rabin, Roni Caryn, Knvul Sheikh, and Katie Thomas. 2020. "As Coronavirus Numbers Rise, C.D.C. Testing Comes Under Fire." *The New York Times*, March 2. Available at: https://www.nytimes.com/2020/03/02/health/coronavirus-testing-cdc.html

Ranney, Megan L., Valerie Griffeth, and Ashish K. Jha. 2020. "Critical Supply Shortages – The Need for Ventilators and Personal Protective Equipment during the Covid-19 Pandemic." *The New England Journal of Medicine*, March 25. Available at: https://www.nejm.org/doi/full/10.1056/NEJMp2006141

Romero, D. 2020 "What are the limits of stay at home orders" NBC News. Available at: https://www.nbcnews.com/news/us-news/what-are-limits-stay-home-orders-n1165391

Rosenthal, Brian M. 2020. "Density Is New York City's Big 'Enemy' in the Coronavirus Fight" *New York Times*. Available at: https://www.nytimes.com/2020/03/23/nyregion/coronavirus-nyc-crowds-density.html

Sandford, Alasdair. 2020. "Coronavirus: Half of Humanity Now on Lockdown as 90 Countries Call for Confinement." *Euronews*, April 2. Available at: https://www.euronews.com/2020/04/02/coronavirus-in-europe-spain-s-death-toll-hits-10-000-after-record-950-new-deaths-in-24-hou

Secon, Holly. 2020. “An Interactive Map Shows How Overloaded Hospitals in the US Could Get as Coronavirus Cases Grow, Region by Region.” *Business Insider*, March 18. Available at: https://www.businessinsider.com/map-shows-hospital-capacity-affected-by-coronavirus-2020-3

Seewer, John. 2020. “U.S. Hospitals Increasingly Worried About Surge in COVID-19 Cases.” *Time*, March 15. Available at: https://time.com/5803605/united-states-hospitals-coronavirus/

Shear, Michael D., Abby Goodnough, Sheila Kaplan, Sheri Fink, Katie Thomas, and Noah Weiland. 2020. “The Lost Month: How a Failure to Test Blinded the U.S. to Covid-19.” *The New York Times*, March 28. Available at: https://www.nytimes.com/2020/03/28/us/testing-coronavirus-pandemic.html

Thackeray, Darren. 2020. “How COVID-19 Compares to Seasonal Flu, and Why You Should Take It Seriously.” *World Economic Forum*, April 1. Available at: https://www.weforum.org/agenda/2020/04/coronavirus-covid19-flu-influenza/

The COVID Tracking Project. 2020. “Most Recent Data.” Available at: https://covidtracking.com

Tsai, Thomas C., Benjamin H. Jacobson, and Ashish K. Jha. 2020. “American Hospital Capacity and Projected Need for COVID-19 Patient Care.” *Health Affairs*, March 17. Available at: https://www.healthaffairs.org/do/10.1377/hblog20200317.457910/full/

U.S. Department of Labor. 2020. “News Release: Unemployment Insurance Weekly Claims.” March 26. Available at: https://www.dol.gov/ui/data.pdf

Verity, Robert, Lucy C. Okell, Ilaria Dorigatti, Peter Winskill, Charles Whittaker, Natsuko Imai, Gina Cuomo-Dannenburg, Hayler Thompson, Patrick G. T. Walker, Han Fu, Amy Dighe, Jamie T. Griffin, Marc Baguelin, Sangeeta Bhatia, Adhiratha Bonyasiri, Anne Cori, Zulma Cucunuba, Rich FitzJohn, Katy Gaythorpe, Will Green, Arran Hamlet, Wes Hinsley, Daniel Laydon, Gemma Nedjati-Gilani, Steven Riley, Sabine van Elsland, Erik Volz, Haowei Wang, Yuanrong Wang, Xiaoyue Xi, Christl A. Donnelly, Azra C. Ghani, Neil M. Ferguson. 2020. “Estimates of The Severity of Coronavirus Disease 2019: A Model-Based Analysis.” *The Lancet: Infectious Diseases*, March 30. Available at: https://www.thelancet.com/journals/laninf/article/PIIS1473-3099(20)30243-7/fulltext

Wang, Dawei, Bo Hu, Chang Hu, Fangfang Zhu, Xing Liu, Jing Zhang, Binbin Wang, Hui Xiang, Zhenshun Cheng, Yong Xiong, Yan Zhao, Yirong Li, Xinghuan Wang, & Zhiyong Peng. 2020. “Clinical Characteristics of 138 Hospitalized Patients With 2019 Novel Coronavirus–Infected Pneumonia in Wuhan, China.” *JAMA.*

Webber, Tammy. 2020. “Residents Snitch on Businesses, Neighbors Amid Shutdowns.” *The Associated Press*, April 2. Available at: https://apnews.com/343ed4a8e95dfc8f8dda87b9e450ca57

Whitehead, Sam. 2020. "CDC Director On Models For The Months To Come: 'This Virus Is Going To Be With Us'." *National Public Radio,* March 31. Available at: https://www.npr.org/sections/health-shots/2020/03/31/824155179/cdc-director-on-models-for-the-months-to-come-this-virus-is-going-to-be-with-us

White House. 2020. "The President's Coronavirus Guidelines for America." Available at: https://www.whitehouse.gov/wp-content/uploads/2020/03/03.16.20_coronavirus-guidance_8.5x11_315PM.pdf

White House Coronavirus Task Force. 2020. "Remarks by President Trump, Vice President Pence, and Members of the Coronavirus Task Force in Press Briefing." April 1. Available at: https://www.whitehouse.gov/briefings-statements/remarks-president-trump-vice-president-pence-members-coronavirus-task-force-press-briefing-15/

Wilson N, Kvalsvig A, Telfar Barnard L, Baker MG. Case-fatality estimates for COVID-19 calculated by using a lag time for fatality. Emerg Infect Dis. 2020 Jun [*date cited*]. https://doi.org/10.3201/eid2606.200320

World Health Organization. 2020a. "Rolling Updates on Coronavirus Disease (COVID-19)." Available at: https://www.who.int/emergencies/diseases/novel-coronavirus-2019/events-as-they-happen

World Health Organization. 2020b. "Q&A: Similarities and Differences – COVID-19 and Influenza." Available at: https://www.who.int/news-room/q-a-detail/q-a-similarities-and-differences-covid-19-and-influenza

World Health Organization. 2020c. "Coronavirus Disease (COVID-19) Advice for the Public." Available at: https://www.who.int/emergencies/diseases/novel-coronavirus-2019/advice-for-public

World Health Organizations. 2020d. "Modes of Transmission of Virus Causing COVID-19: Implications for IPC Precaution Recommendations." Available at: https://www.who.int/news-room/commentaries/detail/modes-of-transmission-of-virus-causing-covid-19-implications-for-ipc-precaution-recommendations

World Health Organization. 2020e. "Shortage of Personal Protective Equipment Endangering Health Workers Worldwide." March 3. Available at: https://www.who.int/news-room/detail/03-03-2020-shortage-of-personal-protective-equipment-endangering-health-workers-worldwide

World Health Organization. 2020f. "Coronavirus Disease 2019 (COVID-19) Situation Report – 46." Available at: https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200306-sitrep-46-covid-19.pdf?sfvrsn=96b04adf

World Population Review. 2020. "US States - Ranked by Population 2020" Available at: https://worldpopulationreview.com/states/

Wu, Zunyou and Jennifer M. McGoogan. 2020. “Characteristics of and Important Lessons From the Coronavirus Disease 2019 (COVID-19) Outbreak in China: Summary of a Report of 72,314 Cases From the Chinese Centers for disease Control and Prevention.” *JAMA*, February 24. Available at: https://jamanetwork.com/journals/jama/fullarticle/2762130

Yancey-Bragg, N’dea. 2020. “Going to a drive-thru COVID-19 Testing Site? Here's a Step-By-Step Look at What to Expect.” *USA Today*, March 20. Available at: https://www.usatoday.com/story/news/health/2020/03/20/drive-thru-coronavirus-testing-step-step-look-what-expect/287332400

Figure 1: COVID-19 Cases Per 100,000 by State, March 12-April 20, 2020

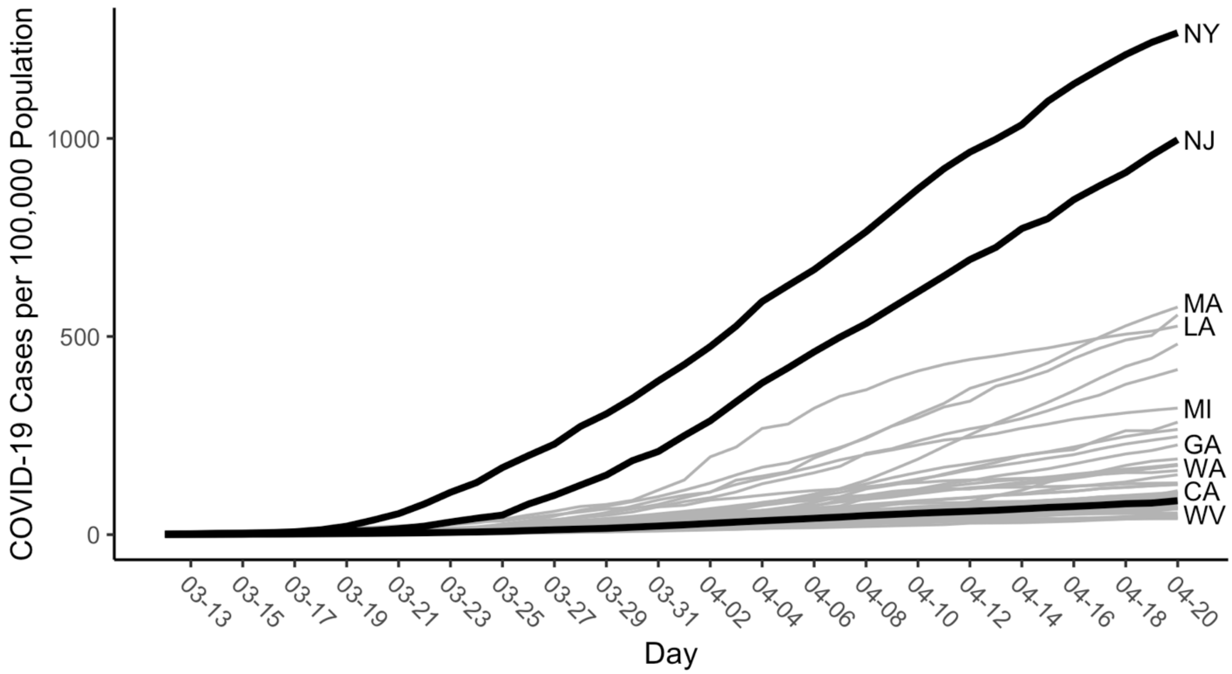


Figure 2: COVID-19 Deaths Per 100,000 by State, March 12-April 20, 2020

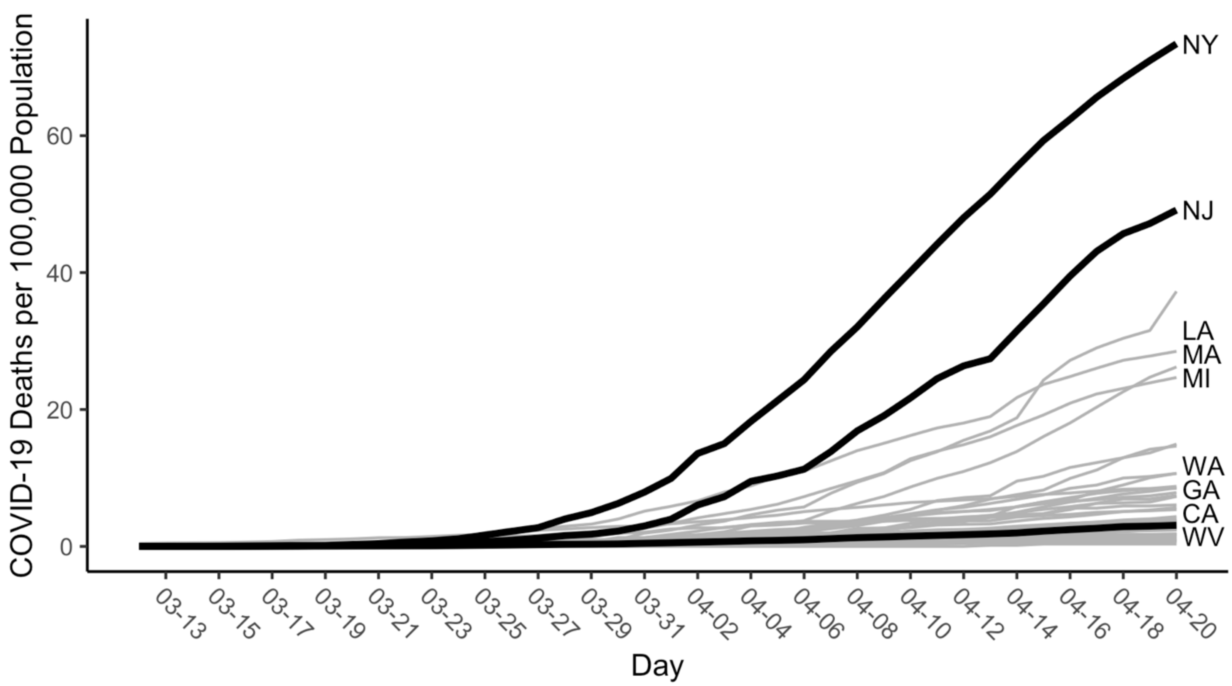


Figure 3: COVID-19 Cases Per 100,000 by California County, March 12-April 20, 2020

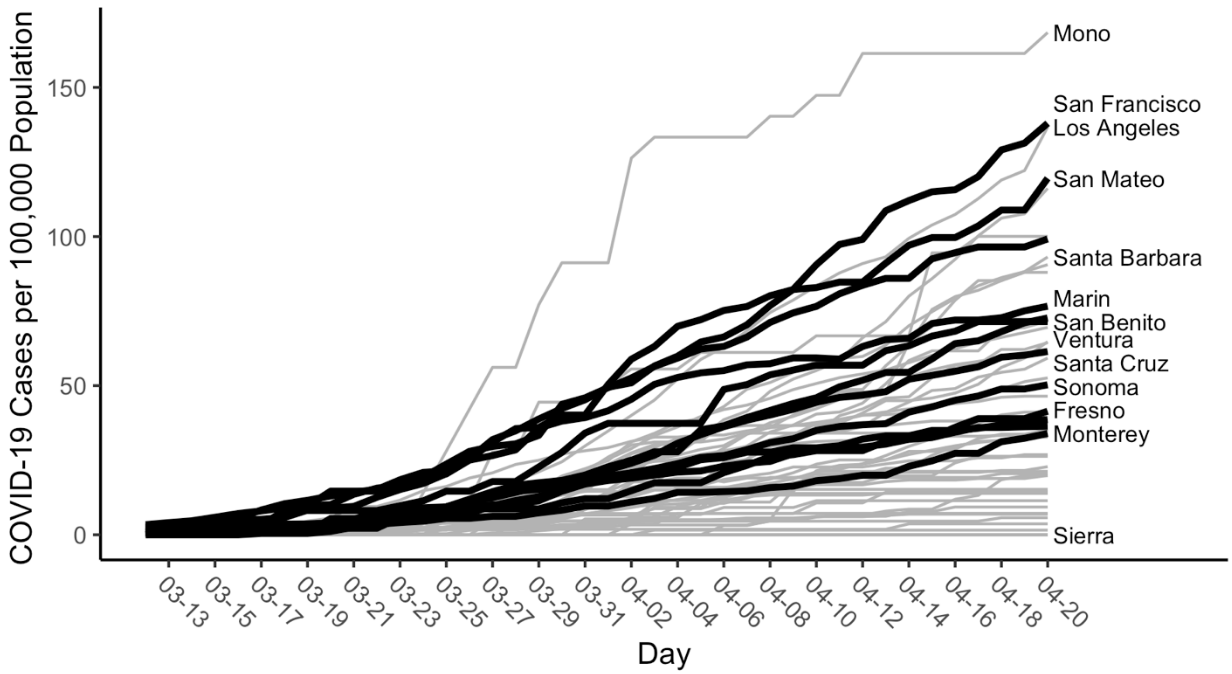
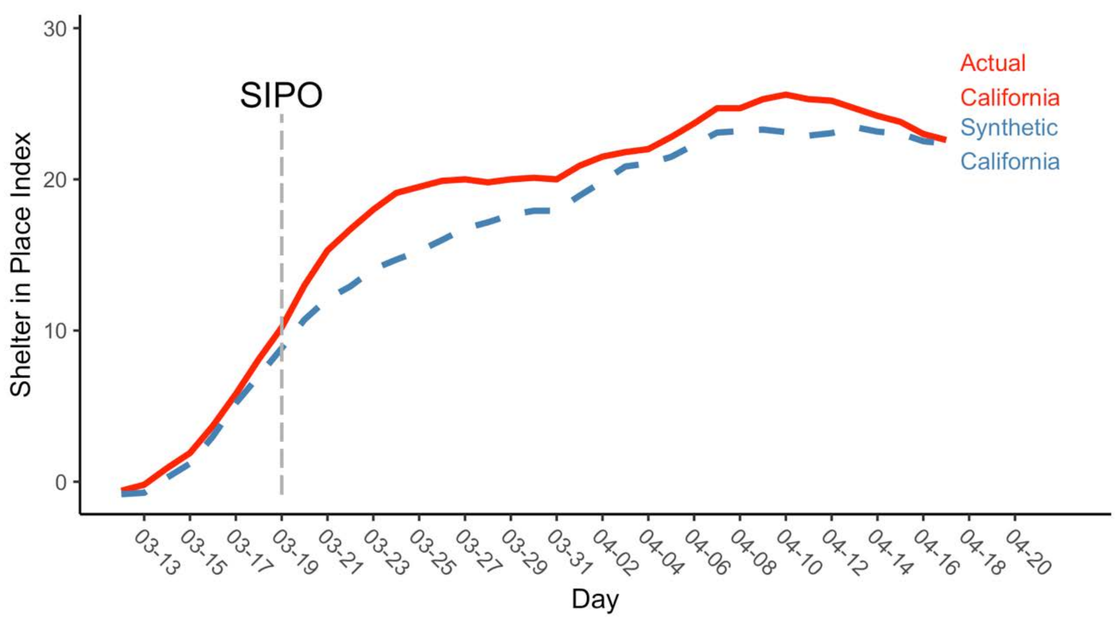


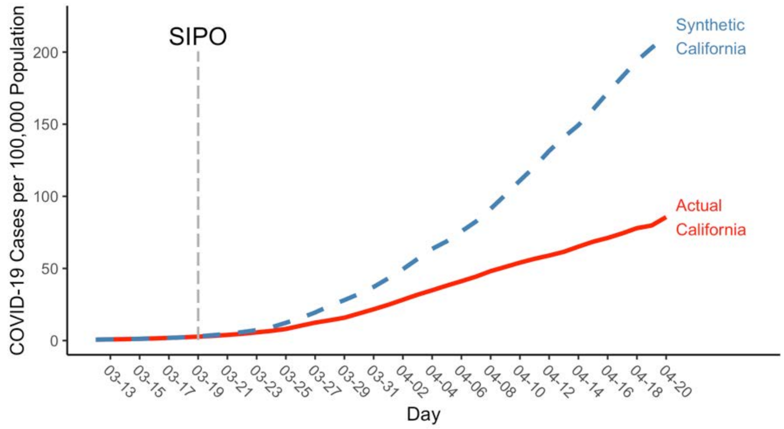
Figure 4: Synthetic Control Estimates for Shelter-in-Place Index
[Matching Variables: Shelter-in-Place Index on All Pre-Treatment Days]



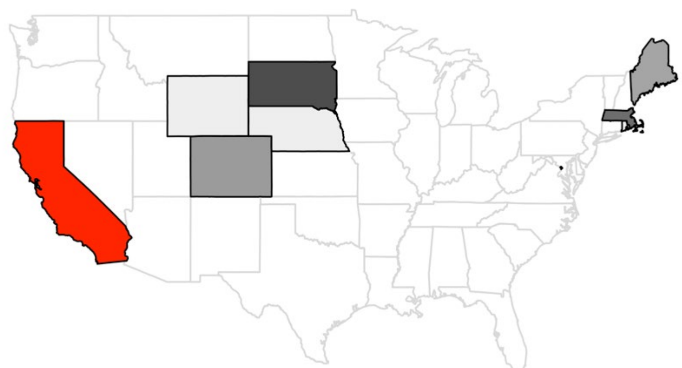
Notes: Estimate is generated using synthetic control methods. The matching was based on seven days of the pre-SIPO shelter-in-place index. Synthetic California is comprised of DC (.666) and MA (.333). P-values are computed using permutation test. Two-sided p-value is .95 and one-sided p-value is .53. However, the p-value generated from a one-sided test of an examination of the March 19 through March 28 is .02.

Figure 5: Synthetic Control Estimates for Cases Per 100,000
[Matching Variables: COVID-19 Cases on All Pre-Treatment Days]

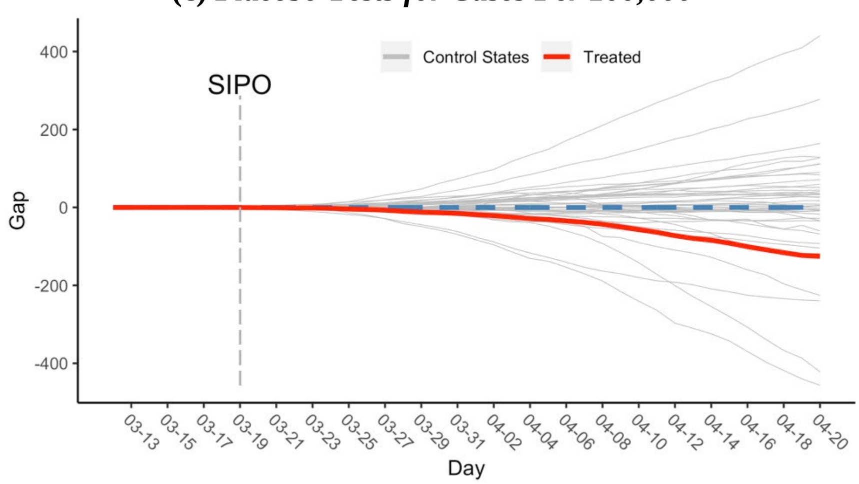
(a) Synthetic California v. Actual California Cases Per 100,000



(b) Donor States for Synthetic California Cases



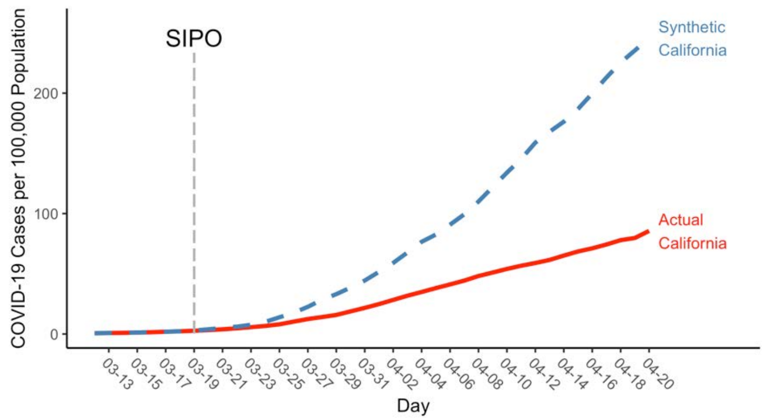
(c) ***Placebo Tests for Cases Per 100,000***



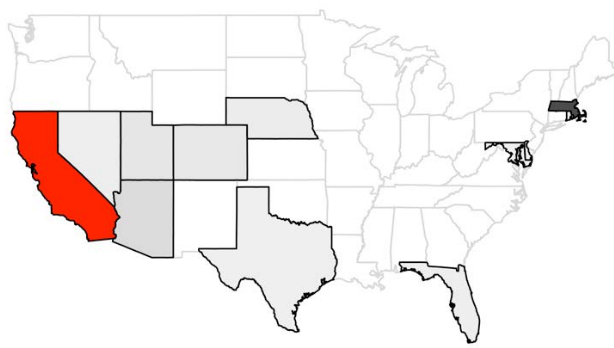
Notes: Estimate is generated using synthetic control methods. The matching was based on seven days of pre-SIPO COVID-19 cases per 100,000. The donor states shaded in Figure 5b are those that received a weight of at least .015 in the estimation of the synthetic control counterfactual for California. Darker shaded states received more weight. Synthetic California is comprised of SD (.177), MA (.148), CO (.106), ME (.096), DC (.029), NE (.017), WY (.017), and RI (.016). In addition, 30 states each contributed a weight between .010 and .015.

Figure 6: Synthetic Control Estimates for Cases Per 100,000
[Matching Variables: COVID-19 Cases on 3 Pre-Treatment Days & Urbanicity]

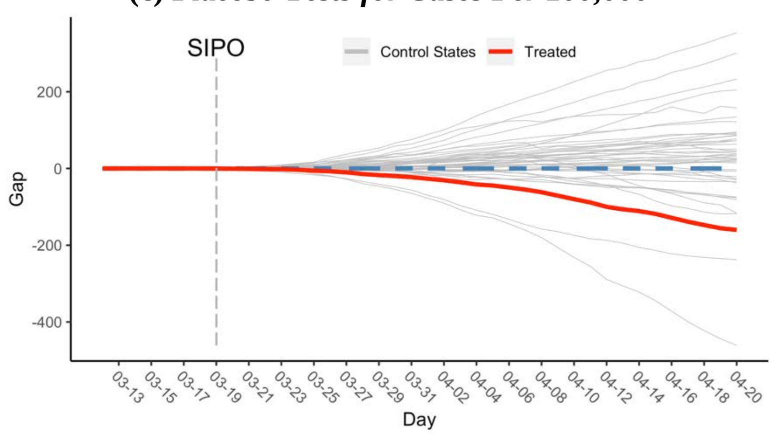
(a) Synthetic California v. Actual California Cases Per 100,000



(b) Donor States for Synthetic California Cases



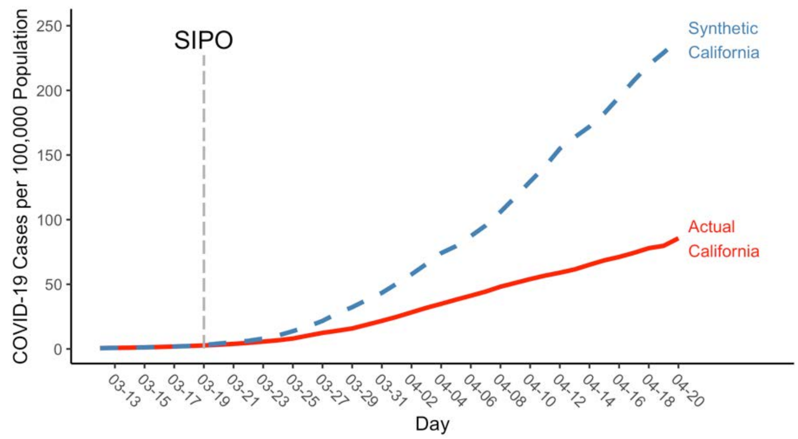
(c) ***Placebo Tests for Cases Per 100,000***



Notes: Estimate is generated using synthetic control methods. The matching was based on three days of pre-SIPO COVID-19 cases per 100,000 and urbanicity measure. The donor states shaded in Figure 6b are those that received a weight of at least .015 in the estimation of the synthetic control counterfactual for California. Darker shaded states received more weight. Synthetic California is comprised of MA (.265), HI (.153), AZ (.051), DC (.036), UT (.033), CO (.031), RI (.028), NE (.022), NV (.021), FL (.019), DE (.017), MD (.017), and TX (.016). In addition, 17 states each contributed a weight between .010 and .015.

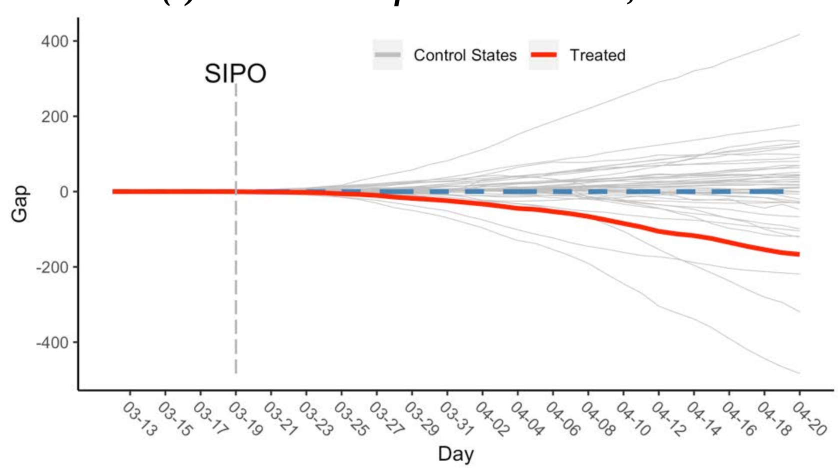
Figure 7: Synthetic Control Estimates for Cases Per 100,000
[Matching Variables: COVID-19 Cases on 3 Pre-Treatment Days, Urbanicity, & Population Density]

(a) Synthetic California v. Actual California Cases Per 100,000



(b) Donor States for Synthetic California Cases

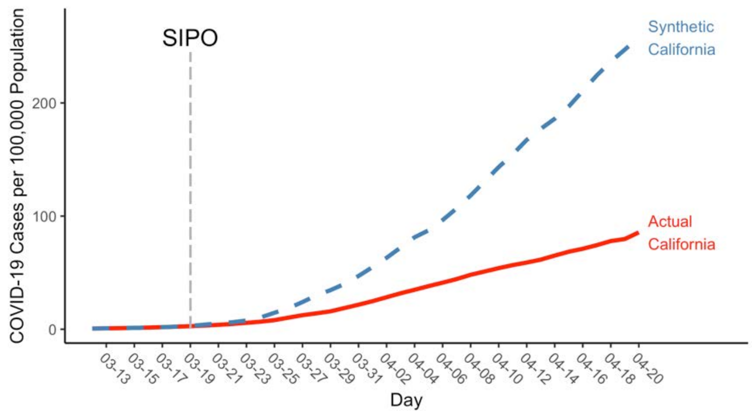
(c) Placebo Tests for Cases Per 100,000



Notes: Estimate is generated using synthetic control methods. The matching was based on three days of pre-SIPO COVID-19 cases per 100,000, urbanicity and population density measure. The donor states shaded in Figure 7b are those that received a weight of at least .015 in the estimation of the synthetic control counterfactual for California. Darker shaded states received more weight. Synthetic California is comprised of HI (.528), MA (.265), NV (.089), RI (.081), and DC (.037).

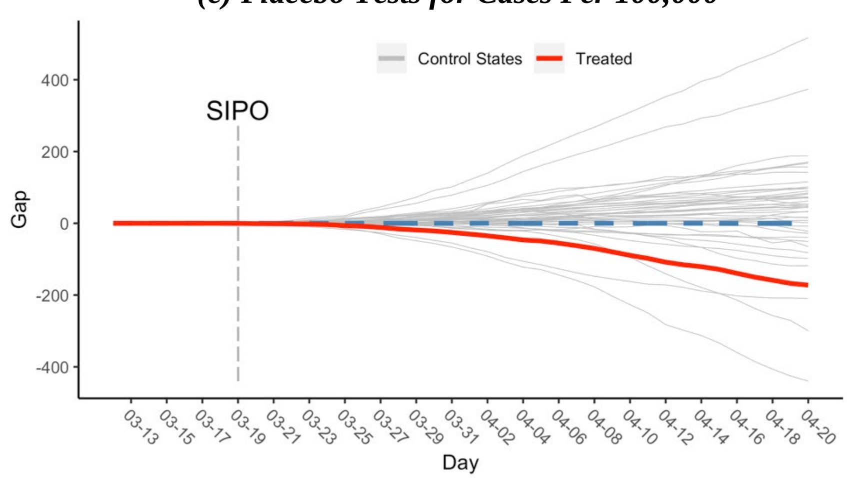
Figure 8: Synthetic Control Estimates for Cases Per 100,000
[Matching Variables: COVID-19 Cases on 3 Pre-Treatment Days & Testing Rate]

(a) Synthetic California v. Actual California Cases Per 100,000



(b) Donor States for Synthetic California Cases

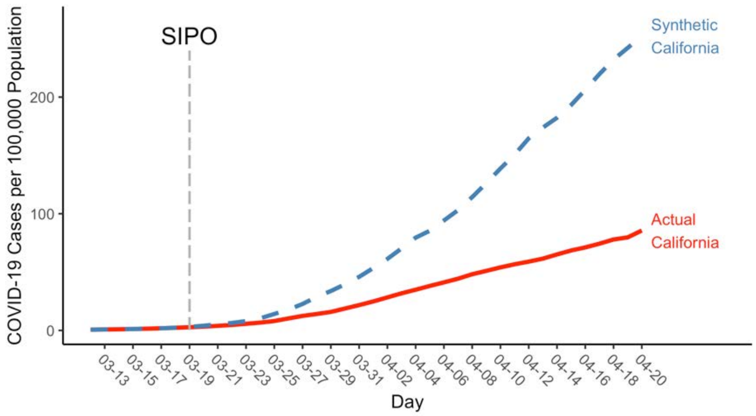
(c) Placebo Tests for Cases Per 100,000



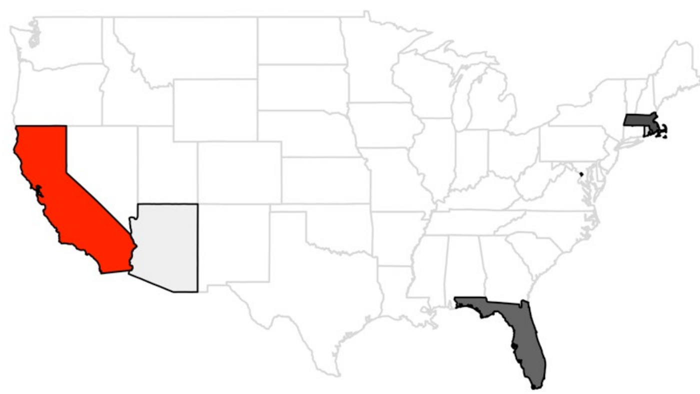
Notes: Estimate is generated using synthetic control methods. The matching was based on three days of pre-SIPO COVID-19 cases per 100,000, and testing per 100,000. The donor states shaded in Figure 8b are those that received a weight of at least .015 in the estimation of the synthetic control counterfactual for California. Darker shaded states received more weight. Synthetic California is comprised of MA (.265), GA (.125), DC (.04), NE (.029), WY (.024), NV (.023), IA (.021), HI (.020), TN (.019), CO (.017), FL (.016), IN (.016), MI (.016), PA (.016), SC (.016) and TX (.016). In addition, 22 states each contributed a weight between .010 and .015.

Figure 9: Synthetic Control Estimates for Cases Per 100,000
[Matching Variables: COVID-19 Cases on 3 Pre-Treatment Days, Urbanicity, Testing Rate, Travel Restriction, & Disaster Emergency]

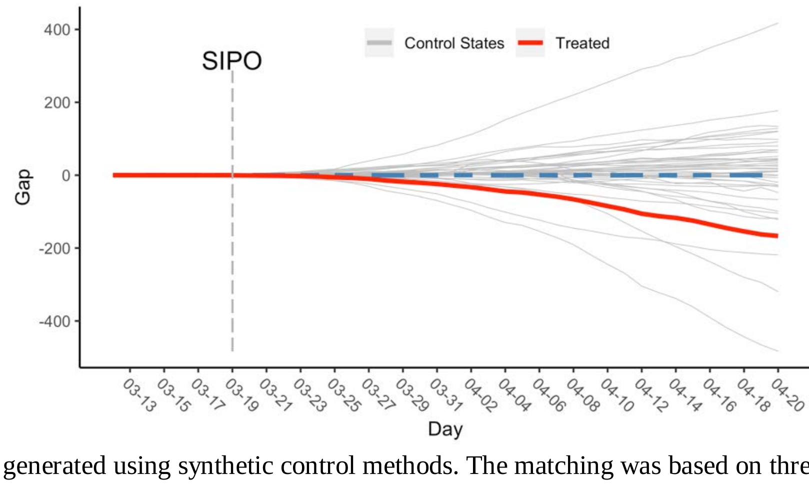
(a) Synthetic California v. Actual California Cases Per 100,000



(b) Donor States for Synthetic California Cases



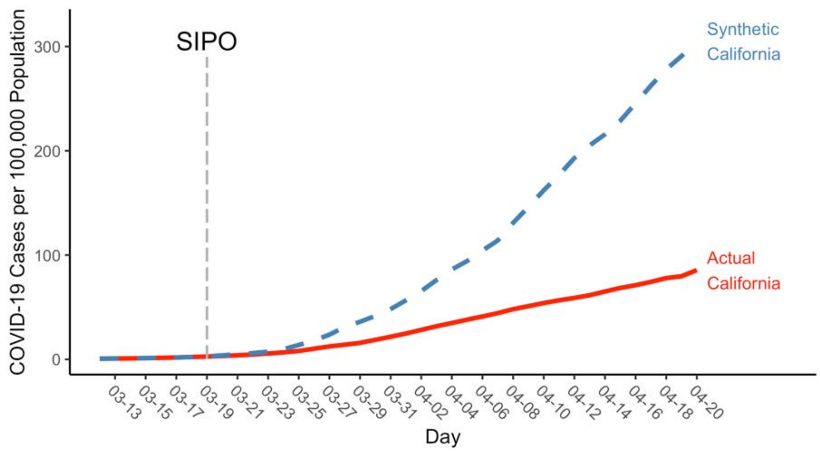
(c) Placebo Tests for Cases Per 100,000



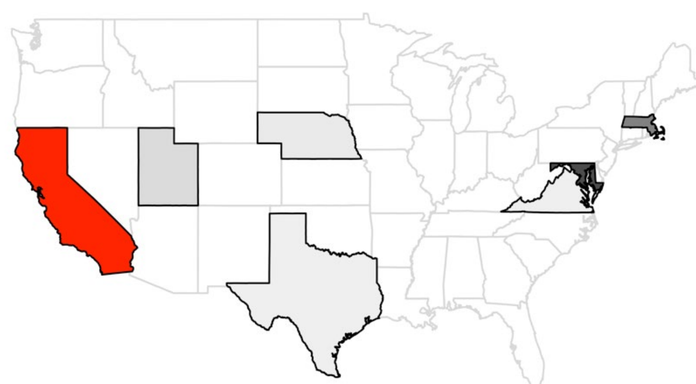
Notes: Estimate is generated using synthetic control methods. The matching was based on three days of pre-SIPO COVID-19 cases per 100,000, urbanicity, testing per 100,000, travel restriction, and disaster emergency. The donor states shaded in Figure 9b are those that received a weight of at least .015 in the estimation of the synthetic control counterfactual for California. Darker shaded states received more weight. Synthetic California is comprised of HI (.357), MA (.261), FL (.231), DC (.067), RI (.061), and AZ (.023).

Figure 10: Synthetic Control Estimates for Cases Per 100,000
[Matching Variables: COVID-19 Cases on 3 Pre-Treatment Days, Shelter in Place Index]

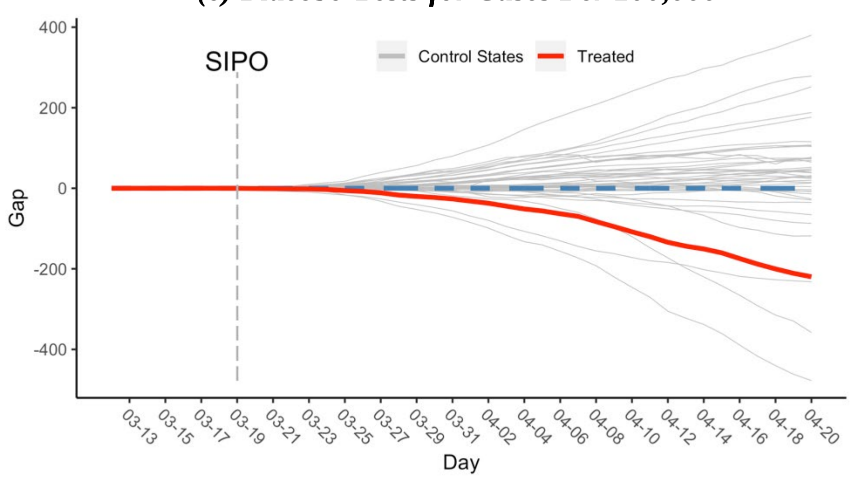
(a) Synthetic California v. Actual California Cases Per 100,000



(b) Donor States for Synthetic California Cases



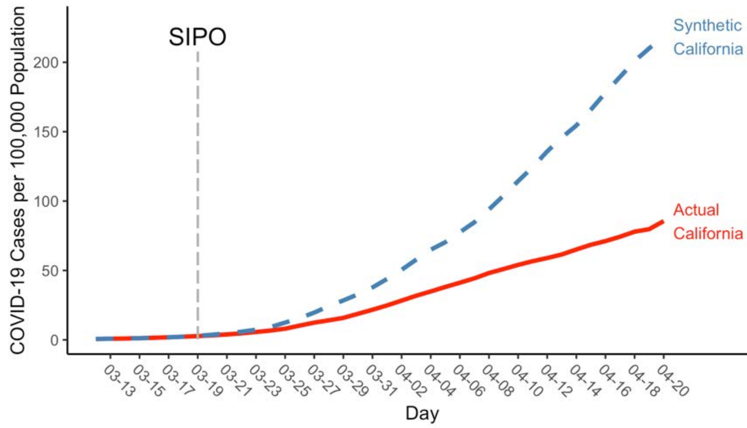
(c) Placebo Tests for Cases Per 100,000



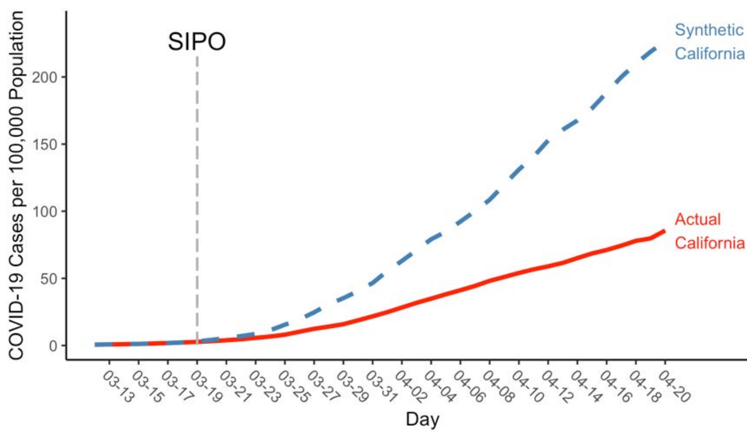
Notes: Estimate is generated using synthetic control methods. The matching was based on three days of pre-SIPO COVID-19 cases per 100,000 and shelter in place index. The donor states shaded in Figure 10b are those that received a weight of at least .015 in the estimation of the synthetic control counterfactual for California. Darker shaded states received more weight. Synthetic California is comprised of MD (.645), MA (.297) and DC (.057).

Figure 11: Synthetic Control Estimates for Testing Per 100,000
[Matching Variables: COVID-19 Testing on All Pre-Treatment Days, Donors with Community Outbreak Prior to California SIPO]

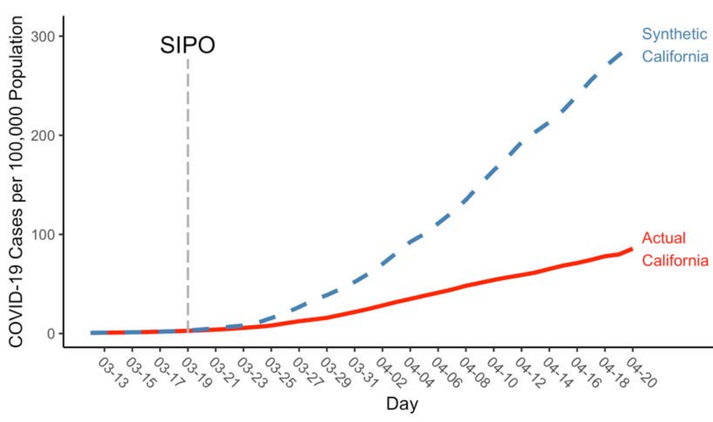
(a) Synthetic California v. Actual California Cases, Pre-Treatment Outbreak Threshold: 10 Cases



(b) Synthetic California v. Actual California Cases, Pre-Treatment Outbreak Threshold: 50 Cases



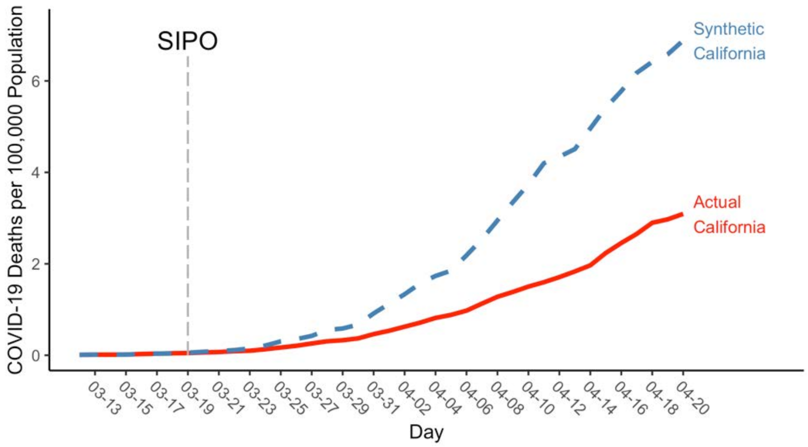
(c) Synthetic California v. Actual California Cases, Pre-Treatment Outbreak Threshold: 100 Cases



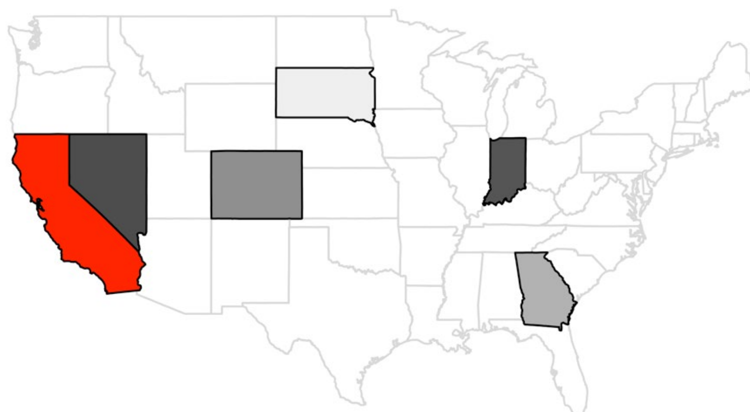
Notes: Estimate is generated using synthetic control methods. The matching was based on three days of pre-SIPO COVID-19 cases per 100,000 and coronavirus outbreak.

Figure 12: Synthetic Control Estimates for Deaths Per 100,000
[Matching Variables: COVID-19 Deaths on All Pre-Treatment Days]

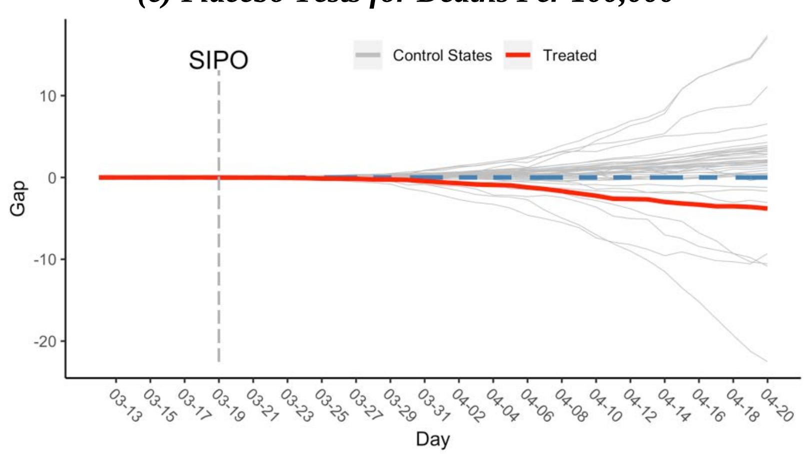
(a) Synthetic California v. Actual California Deaths Per 100,000



(b) Donor States for Synthetic California Deaths



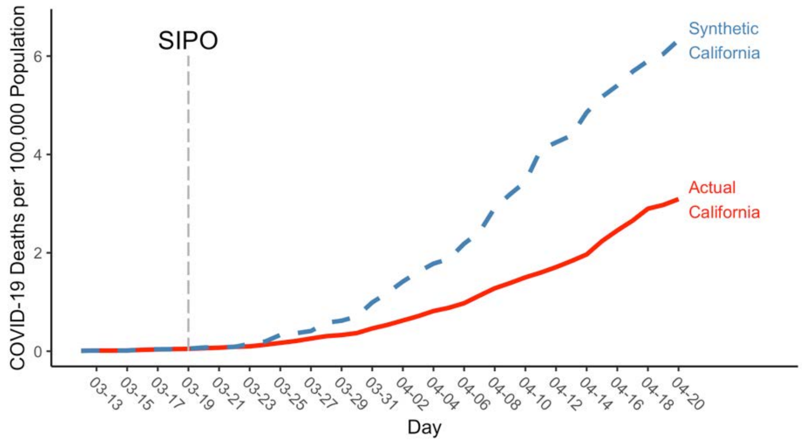
(c) Placebo Tests for Deaths Per 100,000



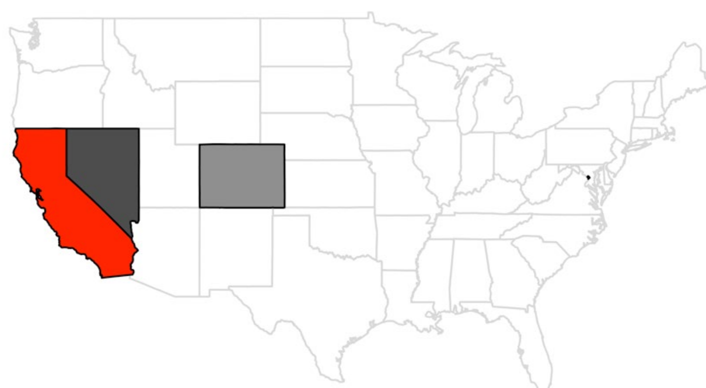
Notes: Estimate is generated using synthetic control methods. The matching was based on three days of pre-SIPO COVID-19 deaths per 100,000. The donor states shaded in Figure 12b are those that received a weight of at least .015 in the estimation of the synthetic control counterfactual for California. Darker shaded states received more weight. Synthetic California is comprised of NV (.302), IN (.292), CO (.208), GA (.152), and SD (.046).

Figure 13: Synthetic Control Estimates for Deaths Per 100,000
[Matching Variables: COVID-19 Deaths on 3 Pre-Treatment Days & Urbanicity]

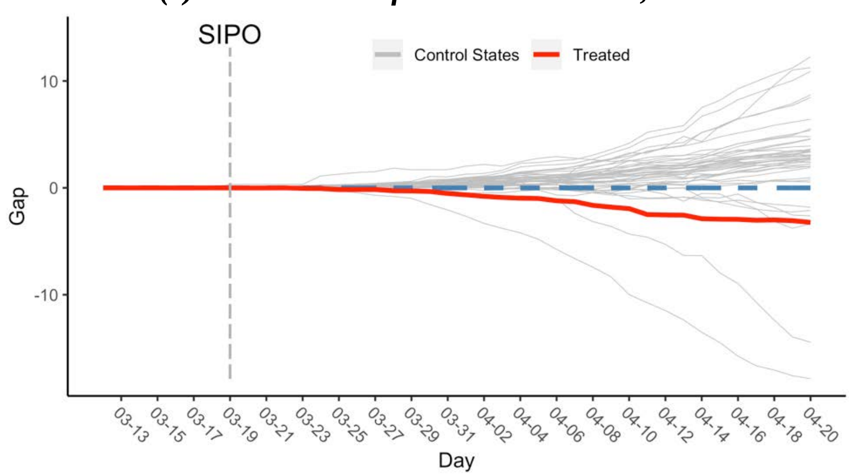
(a) Synthetic California v. Actual California Deaths Per 100,000



(b) Donor States for Synthetic California Deaths



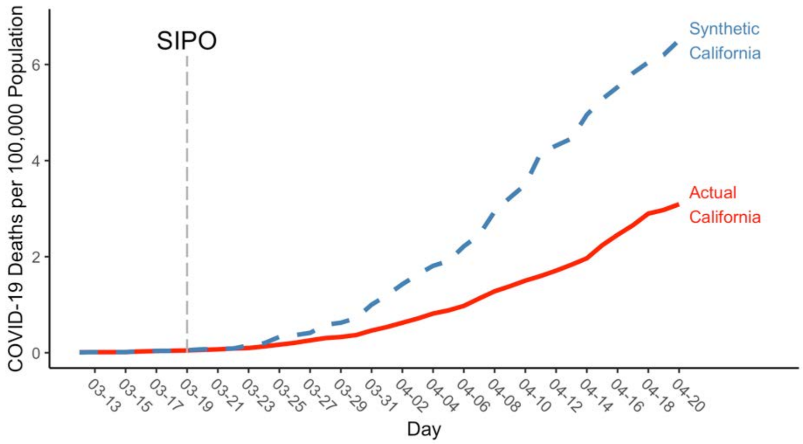
(c) Placebo Tests for Deaths Per 100,000



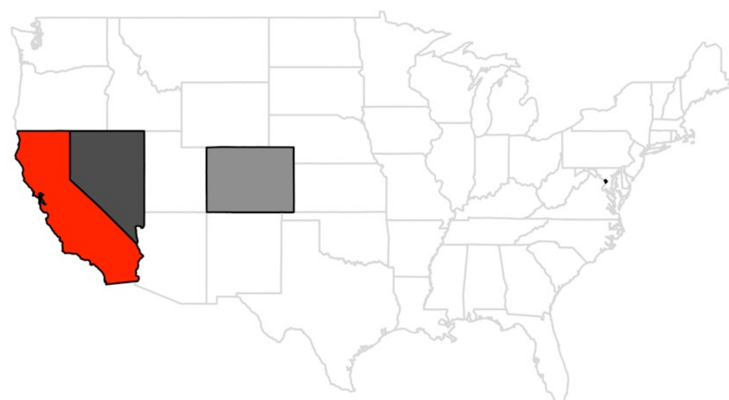
Notes: Estimate is generated using synthetic control methods. The matching was based on three days of pre-SIPO COVID-19 deaths per 100,000, and urbanicity. The donor states shaded in Figure 13b are those that received a weight of at least .015 in the estimation of the synthetic control counterfactual for California. Darker shaded states received more weight. Synthetic California is comprised of NV (0.619) and CO (0.379).

Figure 14: Synthetic Control Estimates for Deaths Per 100,000
[Matching Variables: COVID-19 Deaths on 3 Pre-Treatment Days, Pop Density, & Urbanicity]

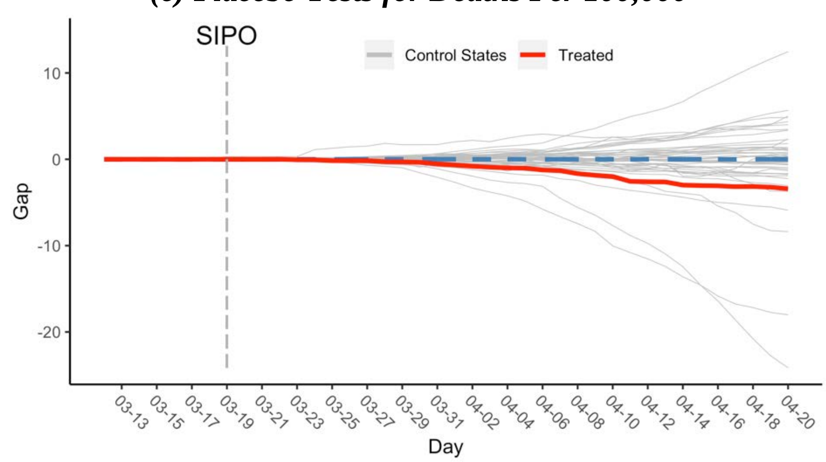
(a) Synthetic California v. Actual California Deaths Per 100,000



(b) Donor States for Synthetic California Deaths



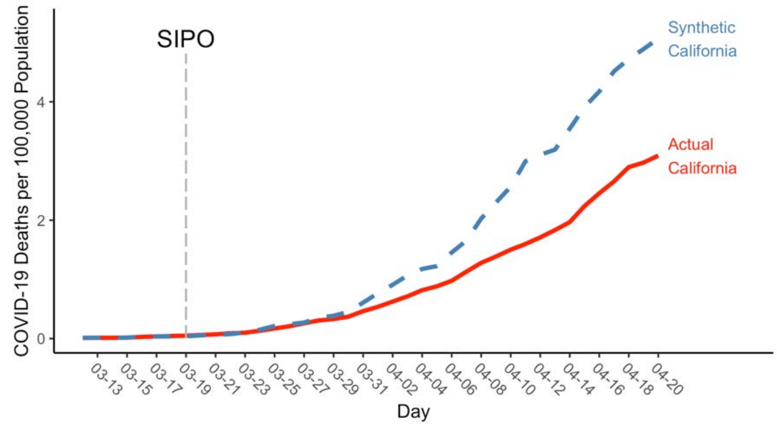
(c) Placebo Tests for Deaths Per 100,000



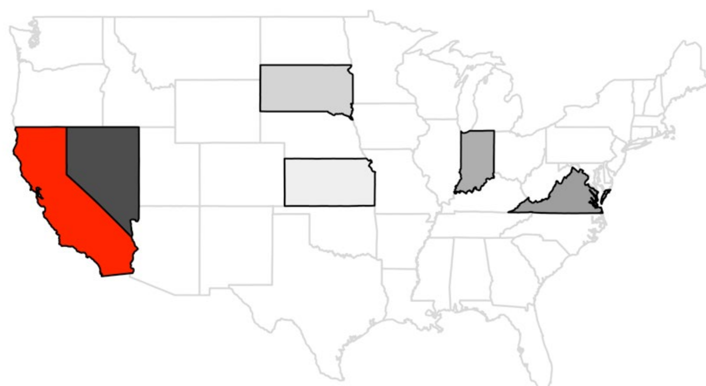
Notes: Estimate is generated using synthetic control methods. The matching was based on three days of pre-SIPO COVID-19 deaths per 100,000, urbanicity, and population density. The donor states shaded in Figure 14b are those that received a weight of at least .015 in the estimation of the synthetic control counterfactual for California. Darker shaded states received more weight. Synthetic California is comprised of NV (0.598), CO (0.385), and DC (.018).

Figure 15: Synthetic Control Estimates for Deaths Per 100,000
[Matching Variables: COVID-19 Deaths on 3 Pre-Treatment Days & Testing Rate]

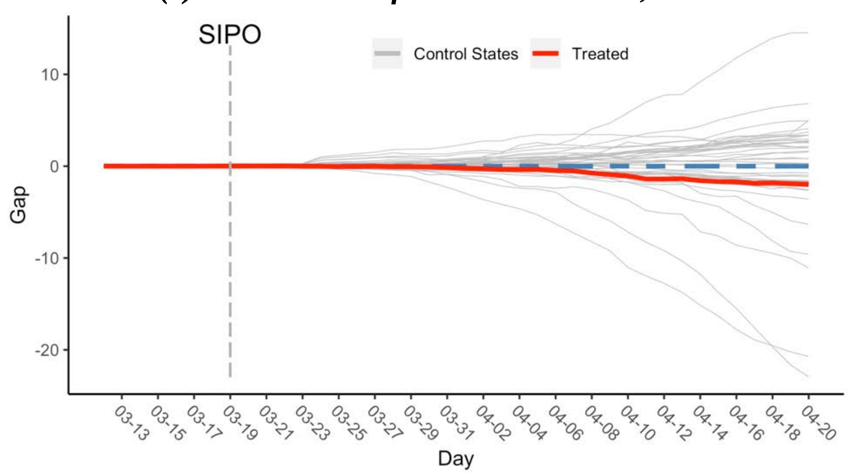
(a) Synthetic California v. Actual California Deaths Per 100,000



(b) Donor States for Synthetic California Deaths



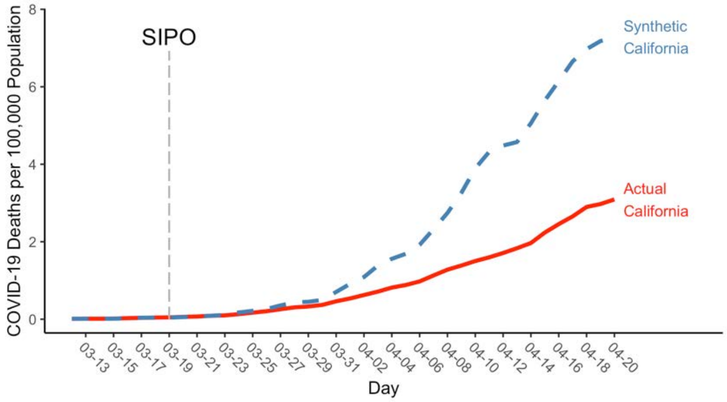
(c) Placebo Tests for Deaths Per 100,000



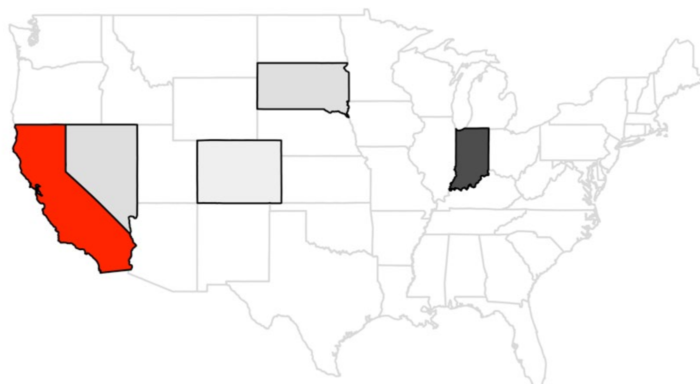
Notes: Estimate is generated using synthetic control methods. The matching was based on three days of pre-SIPO COVID-19 deaths per 100,000 and testing per 100,000. The donor states shaded in Figure 15b are those that received a weight of at least .015 in the estimation of the synthetic control counterfactual for California. Darker shaded states received more weight. Synthetic California is comprised of NV (.368), VA (.215), IN (.181), SD (.098) and KS (.034). In addition, 1 state contributed a weight between .010 and .015.

Figure 16: Synthetic Control Estimates for Deaths Per 100,000
[Matching Variables: COVID-19 Deaths on 3 Pre-Treatment Days, Urbanicity, Testing Rate, Travel Restriction, & Disaster Emergency]

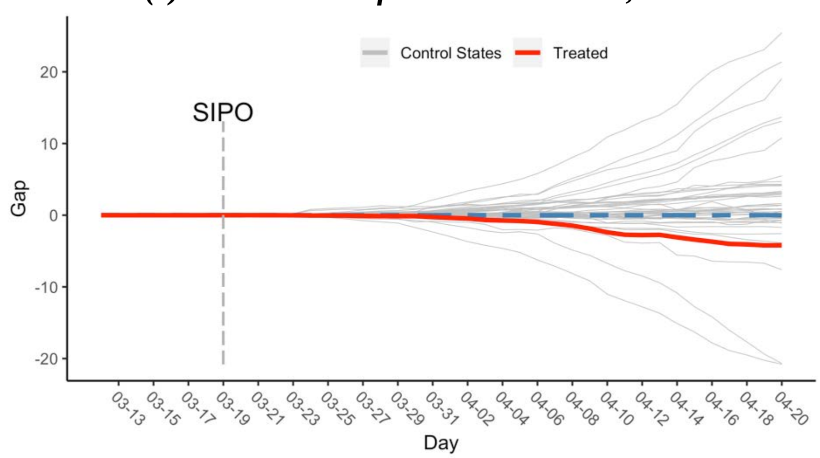
(a) Synthetic California v. Actual California Deaths Per 100,000



(b) Donor States for Synthetic California Deaths



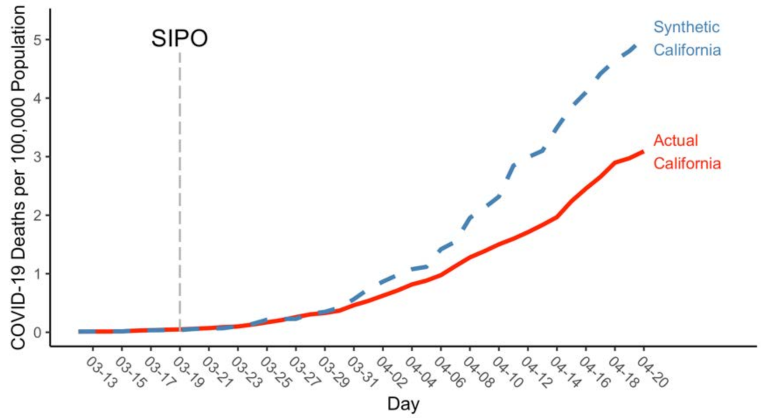
(c) Placebo Tests for Deaths Per 100,000



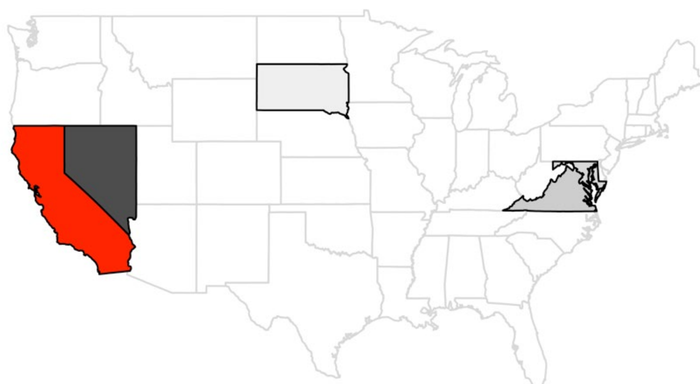
Notes: Estimate is generated using synthetic control methods. The matching was based on three days of pre-SIPO COVID-19 deaths per 100,000, urbanicity, testing per 100,000, travel restriction, and disaster emergency. The donor states shaded in Figure 16b are those that received a weight of at least .015 in the estimation of the synthetic control counterfactual for California. Darker shaded states received more weight. Synthetic California is comprised of IN (.748), NV (.115), SD (.108), and CO (.028).

Figure 17: Synthetic Control Estimates for Deaths Per 100,000
[Matching Variables: COVID-19 Deaths on 3 Pre-Treatment Days, Shelter in Place Index]

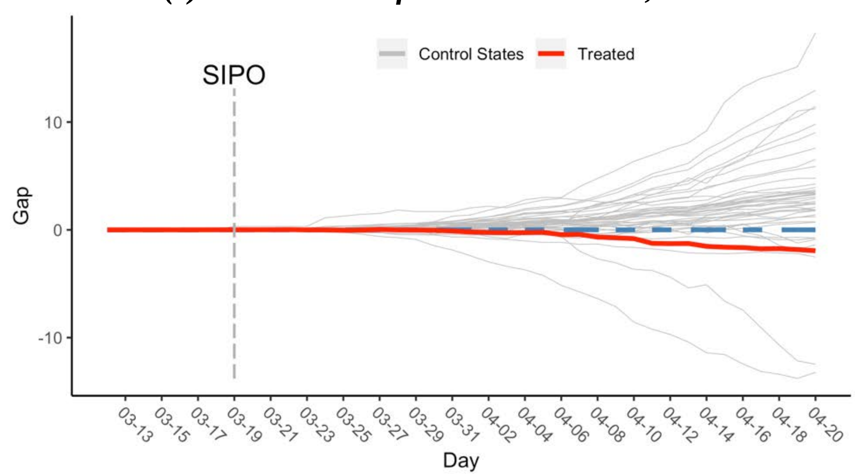
(a) Synthetic California v. Actual California Deaths Per 100,000



(b) Donor States for Synthetic California Deaths



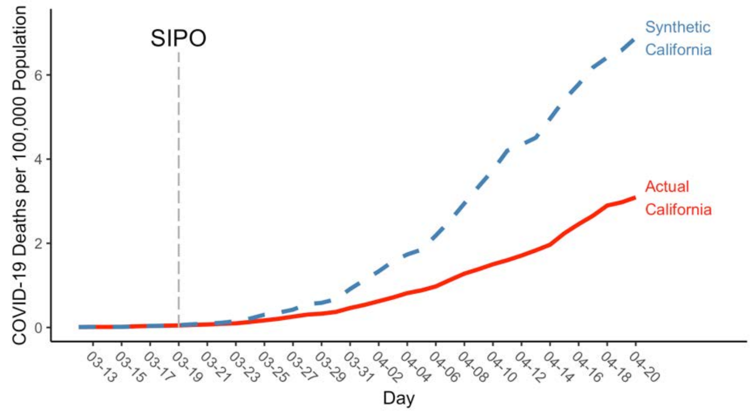
(c) Placebo Tests for Deaths Per 100,000



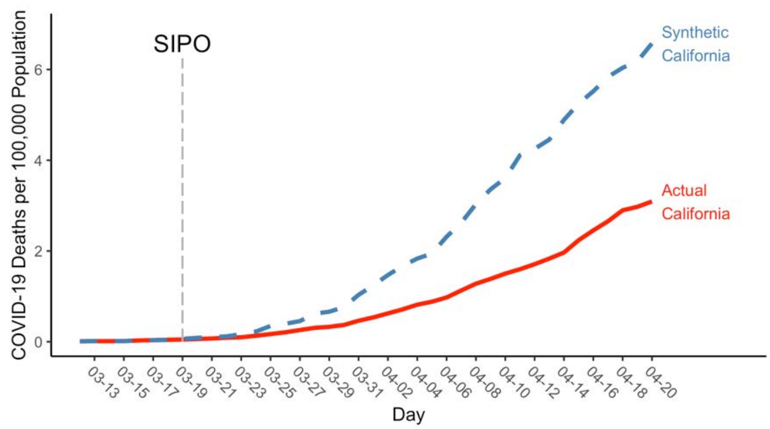
Notes: Estimate is generated using synthetic control methods. The matching was based on three days of pre-SIPO COVID-19 deaths per 100,000 and shelter in place index. The donor states shaded in Figure 17b are those that received a weight of at least .015 in the estimation of the synthetic control counterfactual for California. Darker shaded states received more weight. Synthetic California is comprised of NV (.515), VA (.194), MD (.18), and SD (.112).

Figure 18: Synthetic Control Estimates for Testing Per 100,000
[Matching Variables: COVID-19 Testing on All Pre-Treatment Days, Donors with Community Outbreak Prior to California SIPO]

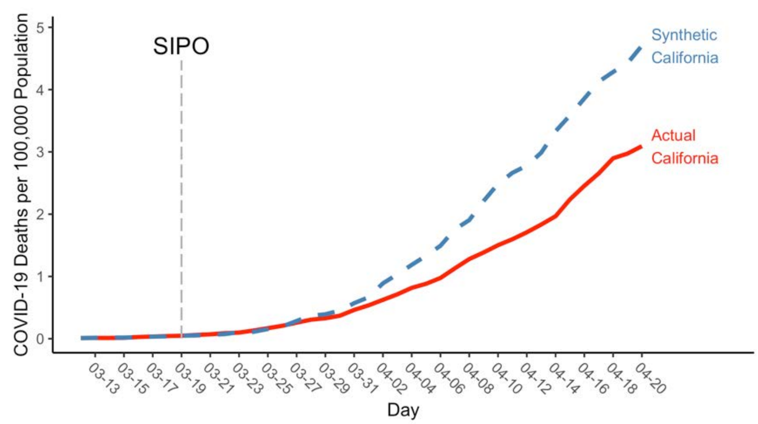
(a) Synthetic California v. Actual California Deaths, Pre-Treatment Outbreak Threshold: 10 Cases



(b) Synthetic California v. Actual California Deaths, Pre-Treatment Outbreak Threshold: 50 Cases



(c) (c) Synthetic California v. Actual California Cases, Pre-Treatment Outbreak Threshold: 100 Cases



Notes: Estimate is generated using synthetic control methods. The matching was based on three days of pre-SIPO COVID-19 cases per 100,000 and coronavirus outbreak.

Table 1: Synthetic Control Estimates of Effect of SIPO on COVID-19 Cases per 100,000 Population

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel I: Post-Treatment Window -- March 19 to April 20					
SIPO	-42.018**	-56.318**	-53.767**	-61.646**	-59.372**	-74.599*
P-Value	[0.045]	[0.023]	[0.068]	[0.023]	[0.045]	[0.068]
One Sided P-Value	[0.045]	[0.023]	[0.045]	[0.023]	[0.045]	[0.068]
	Panel II: Post-Treatment Window -- March 23 to April 20					
SIPO	-47.724**	-63.970**	-61.040*	-70.015**	-67.420**	-84.783*
P-Value	[0.045]	[0.023]	[0.091]	[0.045]	[0.045]	[0.068]
One Sided P-Value	[0.045]	[0.023]	[0.068]	[0.045]	[0.045]	[0.068]
	Panel III: Post-Treatment Window -- March 30 to April 20					
SIPO	-60.958**	-81.576**	-77.828*	-89.254*	-86.035**	-108.723*
P-Value	[0.068]	[0.023]	[0.091]	[0.068]	[0.045]	[0.091]
One Sided P-Value	[0.045]	[0.023]	[0.068]	[0.068]	[0.045]	[0.068]
Observable used to construct the weights						
Pre-SIPO covid-19 Days	7	3	3	3	3	3
Urbanicity	No	Yes	Yes	No	Yes	No
Population Density	No	No	Yes	No	No	No
Testing Rates	No	No	No	Yes	Yes	No
Travel Restriction	No	No	No	No	Yes	No
Disaster Emergency	No	No	No	No	Yes	No
Shelter in Place Index	No	No	No	No	No	Yes

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

Notes: Estimate is generated using synthetic control methods. The number of donor states are 43. The matching was based of the pre-SIPO covid-19 cases per 100,000 and variables listed under each column. The permutation-based p-values are included in brackets below each point estimate.

Table 2: Sensitivity of Synthetic Control Estimates on Cases to Donor State Restriction on Pre-Treatment Community Outbreak

	(1)	(2)	(3)
	Panel I: Post-Treatment Window -- March 19 to April 20		
SIPO	-17.459**	-25.28	-32.854
P-Value	[0.024]	[0.632]	[0.750]
One Sided P-Value	[0.024]	[0.368]	[0.500]
	Panel II: Post-Treatment Window -- March 23 to April 20		
SIPO	-21.172**	-30.604	-39.885
P-Value	[0.024]	[0.632]	[0.750]
One Sided P-Value	[0.024]	[0.368]	[0.500]
	Panel III: Post-Treatment Window -- March 30 to April 20		
SIPO	-30.540**	-43.477	-57.897
P-Value	[0.024]	[0.684]	[0.750]
One Sided P-Value	[0.024]	[0.368]	[0.500]
Observable used to construct the weights			
Pre-SIPO Covid-19 Days	7	7	7
Case Threshold for Community Outbreak	10	50	100
Size of Donor Pool	40	18	7
Weights	SD (.18), MA (.16), ME (.11), CO (.08), DC (.03)	TN (.27), MA (.26), SC (.21), WI (.15), CO (.09), UT (.01)	WI (.32), MA (.30), PA (.28), CO (.05), GA (.05)

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

Notes: Estimate is generated using synthetic control methods. The matching was based off 7 days of pre-SIPO cases per 100,000. The permutation-based p-values are included in brackets below each point estimate.

Table 3: Difference-in-Differences Estimates of the Effect of California's SIPO on Log (COVID-19 Cases)

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel I: Unweighted Estimates					
SIPO	-0.881***	-0.812***	-0.730**	-0.891***	-0.783**	-0.699***
	(0.121)	(0.114)	(0.279)	(0.122)	(0.271)	(0.233)
N	2082	2001	532	2041	573	737
	Panel II: Using Synthetic Weights					
SIPO	-0.609	-0.623	-0.439	-0.688	-0.589	-0.778
	[-1.131, -0.266]	[-1.116, -0.117]	[-1.22, 0.321]	[-1.196, -0.173]	[-1.186, 0.24]	[-1.316, 0.407]
N	1752	1673	240	1712	280	440
	Panel III: Using Synthetic Weights					
March 19-22	-0.241	-0.367	-0.411	-0.338	-0.458	-0.369
	[-0.93, 0.504]	[-1.056, 0.337]	[-1.146, 0.481]	[-0.884, 0.355]	[-1.149, 0.435]	[-0.86, 0.273]
March 23-29	-0.668***	-0.602**	-0.347	-0.68***	-0.52*	-0.493***
	[-1.078, -0.303]	[-1.073, -0.079]	[-1.246, 0.302]	[-1.145, -0.149]	[-1.228, 0.134]	[-0.787, -0.231]
March 30+	-0.708***	-0.749***	-0.505	-0.818***	-0.783**	-0.964
	[-1.156, -0.336]	[-1.169, -0.352]	[-1.252, 0.236]	[-1.251, -0.37]	[-1.427, -0.008]	[-1.588, 0.346]
N	1752	1673	240	1712	280	440

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

Notes: Regressions include California and each donor state that included positive weights greater than 0.005. All estimates include: an indicator for a non-essential business closure order or a targeted SIPO in a given state-day, indicator for whether a state has issued a travel ban, indicator for whether a state declared a disaster emergency, an indicator for precipitation, average temperature, average precipitation, state and day fixed effects. Standard errors, clustered at the state-level, are reported in parenthesis. Confidence intervals, created using standard errors generated from wild cluster bootstrapping, are reported in brackets.

Table 4: Synthetic Control Estimates of Effect of SIPO on COVID-19 Deaths per 100,000 Population

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel I: Post-Treatment Window -- March 19 to April 20					
SIPO	-1.403	-1.301*	-1.346	-0.679	-1.415	-0.616
P-Value	[0.860]	[0.767]	[0.837]	[0.930]	[0.884]	[0.884]
One Sided P-Value	[0.209]	[0.093]	[0.372]	[0.349]	[0.326]	[0.140]
	Panel II: Post-Treatment Window -- March 23 to April 20					
SIPO	-1.594	-1.479*	-1.530	-0.774	-1.611	-0.703
P-Value	[0.860]	[0.791]	[0.837]	[0.930]	[0.884]	[0.884]
One Sided P-Value	[0.209]	[0.093]	[0.372]	[0.349]	[0.326]	[0.140]
	Panel III: Post-Treatment Window -- March 30 to April 20					
SIPO	-2.052	-1.897*	-1.964	-1.011	-2.100	-0.923
P-Value	[0.860]	[0.814]	[0.837]	[0.953]	[0.884]	[0.907]
One Sided P-Value	[0.209]	[0.093]	[0.372]	[0.349]	[0.326]	[0.140]
Observable used to construct the weights						
Pre-SIPO covid-19 Days	7	3	3	3	3	3
Urbanicity	No	Yes	Yes	No	Yes	No
Population Density	No	No	Yes	No	No	No
Testing Rates	No	No	No	Yes	Yes	No
Travel Restriction	No	No	No	No	Yes	No
Disaster Emergency	No	No	No	No	Yes	No
Shelter in Place Index	No	No	No	No	No	Yes

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

Notes: Estimate is generated using synthetic control methods. The number of donor states are 43. The matching was based of the pre-SIPO covid-19 deaths per 100,000 and variables listed under each column. The permutation-based p-values are included in brackets below each point estimate.

Table 5: Sensitivity of Synthetic Control Estimates on Deaths to Donor State Restriction on Pre-Treatment Community Outbreak

	(1)	(2)	(3)
	Panel I: Post-Treatment Window -- March 19 to April 20		
SIPO	-44.430**	-53.799	-75.255
P-Value	[0.049]	[0.421]	[0.625]
One Sided P-Value	[0.049]	[0.211]	[0.375]
	Panel II: Post-Treatment Window -- March 23 to April 20		
SIPO	-50.467**	-61.037	-85.467
P-Value	[0.049]	[0.474]	[0.625]
One Sided P-Value	[0.049]	[0.263]	[0.375]
	Panel III: Post-Treatment Window -- March 30 to April 20		
SIPO	-64.522**	-77.157	-108.976
P-Value	[0.049]	[0.526]	[0.625]
One Sided P-Value	[0.049]	[0.263]	[0.375
Observable used to construct the weights			
Pre-SIPO Covid-19 Days	7	7	7
Case Threshold for Community Outbreak	10	50	100
Size of Donor Pool	40	18	7
Weights	NV (.30), IN (.30), CO (.21), GA (.15), SD (.05)	NV (.43), CO (.35), GA (.19), FL (.03)	FL (.79), CO (.21)

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

Notes: Estimate is generated using synthetic control methods. The matching was based off 7 days of pre-SIPO cases per 100,000. The permutation-based p-values are included in brackets below each point estimate.

Table 6: Difference-in-Differences Estimates of the Effect of California's SIPO on COVID-Related Deaths

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel I: Difference-in-Difference Estimates on Log (Death Rate): Post-Treatment -- March 19 to April 20					
SIPO	-0.134	-0.192***	-0.191	0.752	1.053	0.756
	[-0.768, 2.491]	[-0.199, -0.18]	[-0.949, 0.673]	[-0.421, 2.185]	[-1.16, 5.204]	[-1.892, 2.898]
N	232	116	147	304	192	188
	Panel II: Difference-in-Difference Estimates on Log (Death Rate): Lagged Effect, Post-Incubation and ARDS					
March 19-29	0.003	0.021***	0.028	0.661	0.9	0.986
	[-0.641, 2.129]	[-0.027, 0.05]	[0.005, 0.075]	[-0.397, 1.968]	[-1.837, 2.146]	[-0.354, 2.55]
March 30+	-0.195	-0.350***	-0.354***	0.775	1.12	0.633
	[-0.809, 2.696]	[-0.66, -0.527]	[-0.778, -0.034]	[-4.09, 2.643]	[-3.986, 10.763]	[-2.892, 3.188]
N	232	116	147	304	192	188
	Panel III: Poisson Estimates on Count of COVID-19 Deaths: Post-Treatment -- March 19 to April 20[a]					
SIPO	-1.112**	-0.598***	-0.597***	-0.747	-1.319	-0.541
	(0.279)	(0.121)	(0.113)	(0.368)	(0.245)	(0.355)
N	240	120	160	320	200	200
	Panel IV: Poisson Estimates on Count of COVID-19 Deaths: Lagged Effect, Post-Incubation and ARDS[a]					
March 19-29	-0.942**	-0.464***	-0.461***	-0.349	-0.991	-0.217
	(0.276)	(0.194)	(0.177)	(0.236)	(0.22)	(0.399)
March 30+	-1.14**	-0.721***	-0.719***	-0.619*	-1.336	-0.841
	(0.263)	(0.194)	(0.181)	(0.343)	(0.226)	(0.609)
N	240	120	160	320	200	200

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

Notes: Regressions include California and each donor state that included positive weights greater than 0.005. All estimates include: an indicator for a non-essential business closure order or a targeted SIPO in a given state-day, indicator for whether a state has issued a travel ban, indicator for whether a state declared a disaster emergency, indicator for any precipitation, average temperature, average precipitation, state and day fixed effects. Confidence intervals, created using standard errors generated from wild cluster bootstrapping, are reported in brackets. [a]Poisson estimates use state population as exposure variable.

Table 7: Means of COVID-19 Cases per 100,000 Population, by Whether County had Local SIPOs Prior to Statewide Order on March 17 (Early Shelter-in-place Order or ESIPO)

	Early County SIPO Adopters	*Counties Bound by Statewide SIPO*
	(1)	(3)
March 12 (5 days pre-ESIPO)	1.819	0.277
March 15 (2 days pre-ESIPO)	2.977	0.670
March 22 (5 days post-ESIPO)	9.213	3.295
March 27 (10 days post-ESIPO)	19.489	10.273
April 9 (23 days post-ESIPO)	52.850	50.150

Notes: Means are weighted using county population.

Table 8: Synthetic Control Methods for Local California Policy for Selected Counties on Cases per 100,000

	(1)	(2)	(3)	(4)	(5)	(6)
	Alameda[a]	Contra Costa	Marin	Monterey	San Benito	San Francisco
SIPO	1.131	0.632	2.424	-1.36	1.144	4.387
P-Value	[0.809]	[0.957]	[0.957]	[0.660]	[1.000]	[0.872]
One Sided P-Value	[0.452]	[0.301]	[0.301]	[0.255]	[0.340]	[0.387]

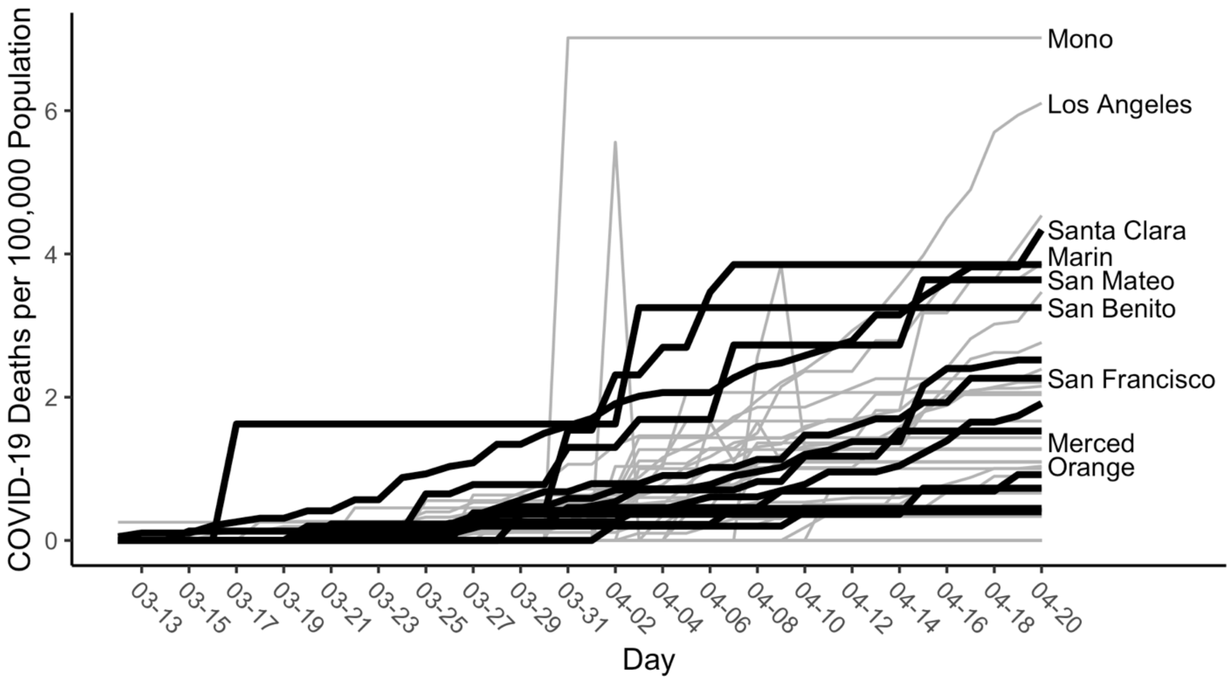
	(7)	(8)	(9)	(10)	(11)	(12)
	San Mateo	Santa Clara	Santa Cruz	Solano	Sonoma	Ventura
SIPO	4.045	3.534	-0.200*	-0.16	-0.655	-0.19
P-Value	[0.957]	[0.957]	[0.064]	[1.000]	[0.702]	[0.681]
One Sided P-Value	[0.301]	[0.301]	[1.000]	[0.340]	[0.255]	[0.255]
Observable used to construct the weights						
Pre-SIPO covid-19 Days	7	7	7	7	7	7

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

Notes: Estimate is generated using synthetic control methods. The matching was based of the pre-SIPO covid-19 cases per 100,000. The permutation-based p-values are included in brackets below each point estimate.

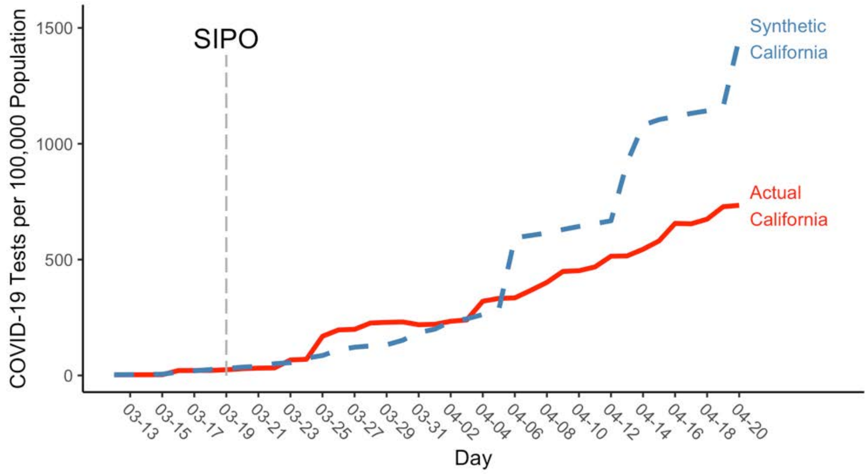
[a] Berkeley City is part of Alameda County.

Appendix Figure 1: Deaths Per 100,000 by California County

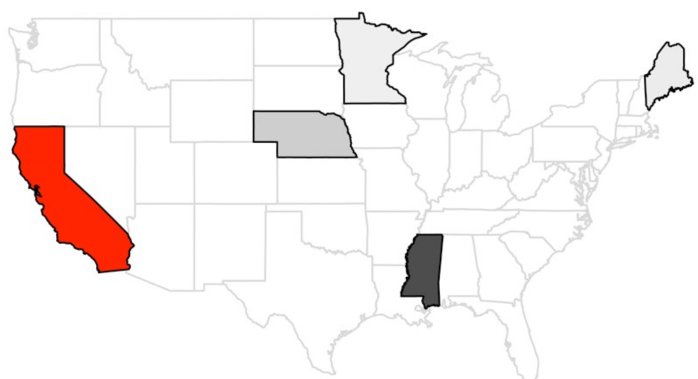


Appendix Figure 2: Synthetic Control Estimates for Testing Per 100,000
[Matching Variables: COVID-19 Testing on All Pre-Treatment Days]

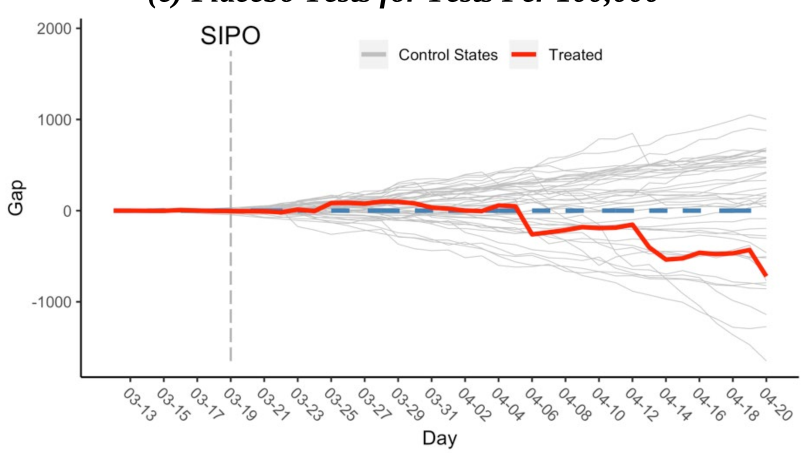
(a) Synthetic California v. Actual California Tests Per 100,000



(b) Donor States for Synthetic California Tests



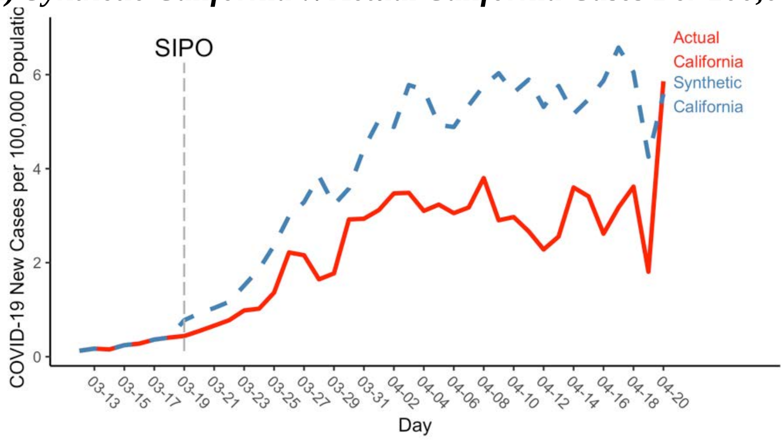
(c) Placebo Tests for Tests Per 100,000



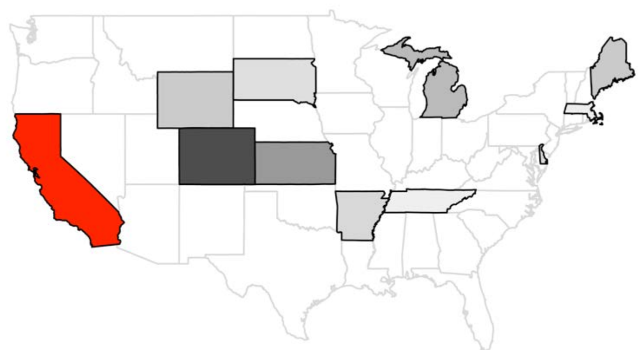
Notes: Estimate is generated using synthetic control methods. The matching was based on seven days of pre-SIPO COVID-19 testing per 100,000. The donor states shaded in Figure Appendix Figure 2b are those that received a weight of at least .015 in the estimation of the synthetic control counterfactual for California. Darker shaded states received more weight. Synthetic California is comprised of MS (.681), NE (.198), ME (.068), and MN (.053).

Appendix Figure 3: Synthetic Control Estimates for Daily Case Rate [Matching Variables: COVID-19 Cases on All Pre-Treatment Days]

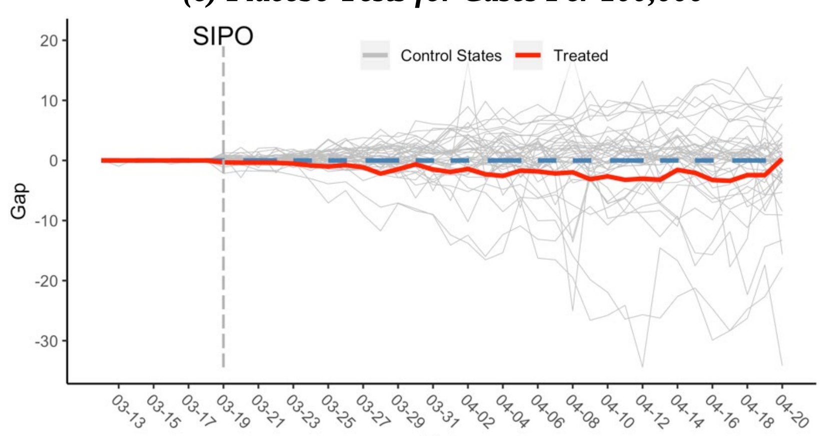
(a) Synthetic California v. Actual California Cases Per 100,000



(b) Donor States for Synthetic California Cases



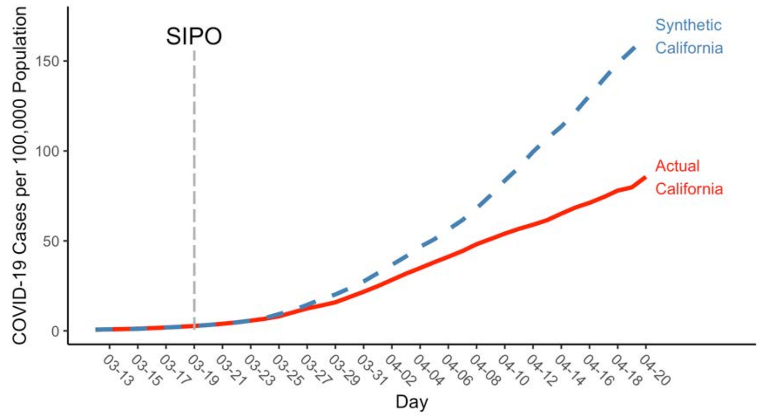
(c) Placebo Tests for Cases Per 100,000



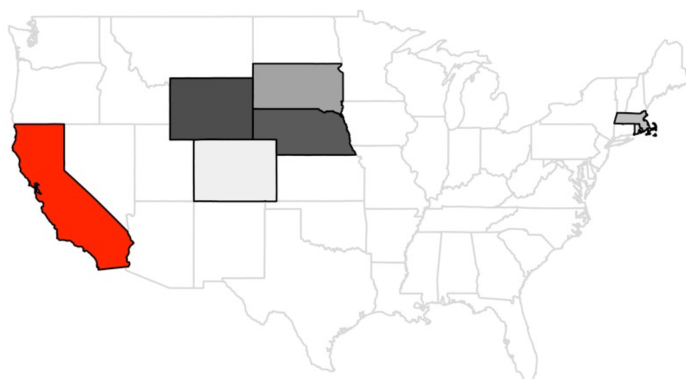
Notes: Estimate is generated using synthetic control methods. The matching was based on seven days of pre-SIPO daily COVID-19 cases per 100,000. The donor states shaded in Appendix Figure 3b are those that received a weight of at least .015 in the estimation of the synthetic control counterfactual for California. Darker shaded states received more weight. Synthetic California is comprised of CO (.201), KS (.122), MI (.083), ME (.064), WY (.062), AK(.055), AR (.046), DE (.041), SD (.037), MA (.017), and TN (.016). In addition, 7 states each contributed a weight between .010 and .015.

Appendix Figure 4: Synthetic Control Estimates for Cases Per 100,000
Forced Match Through Incubation Period
[Matching Variables: COVID-19 Cases on 3 Pre-Treatment & 2 Post-Treatment Days & Urbanicity]

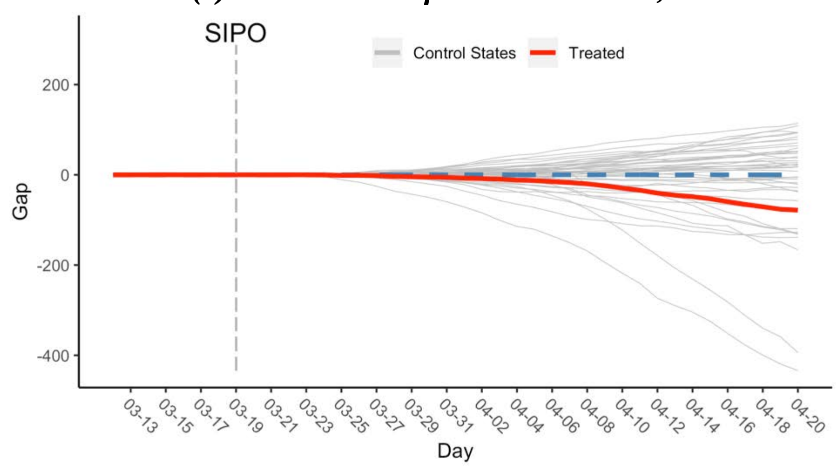
(a) Synthetic California v. Actual California Cases Per 100,000



(b) Donor States for Synthetic California Cases

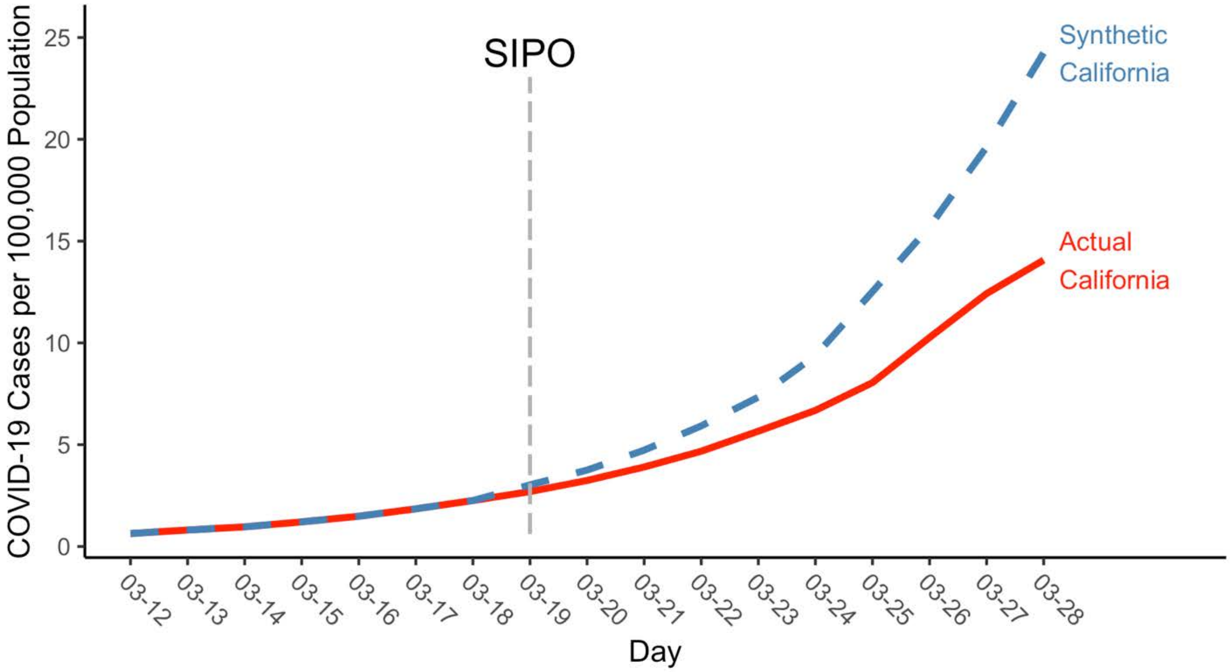


(c) Placebo Tests for Cases Per 100,000



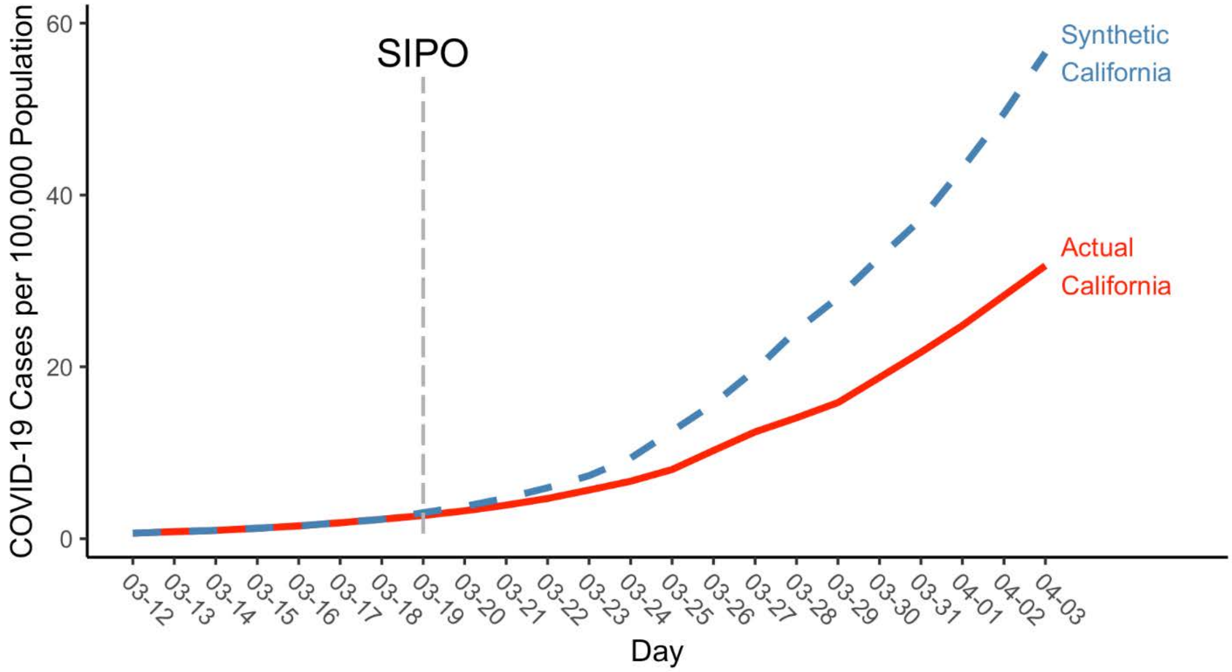
Notes: Estimate is generated using synthetic control methods. The matching was based on seven days of pre-SIPO COVID-19 testing per 100,000. The donor states shaded in Appendix Figure 4b are those that received a weight of at least .015 in the estimation of the synthetic control counterfactual for California. Darker shaded states received more weight. Synthetic California is comprised of WY (.210), NE (.198), SD (.119), MA (.087), RI (.046), and CO (.025). In addition, 9 states contributed a weight between .010 and .015.

Appendix Figure 5: Synthetic Control Estimates for Cases Per 100,000 Limited Post Treatment Window Between March 12 and March 28 [Matching Variables: COVID-19 Cases on All Pre-Treatment Days]



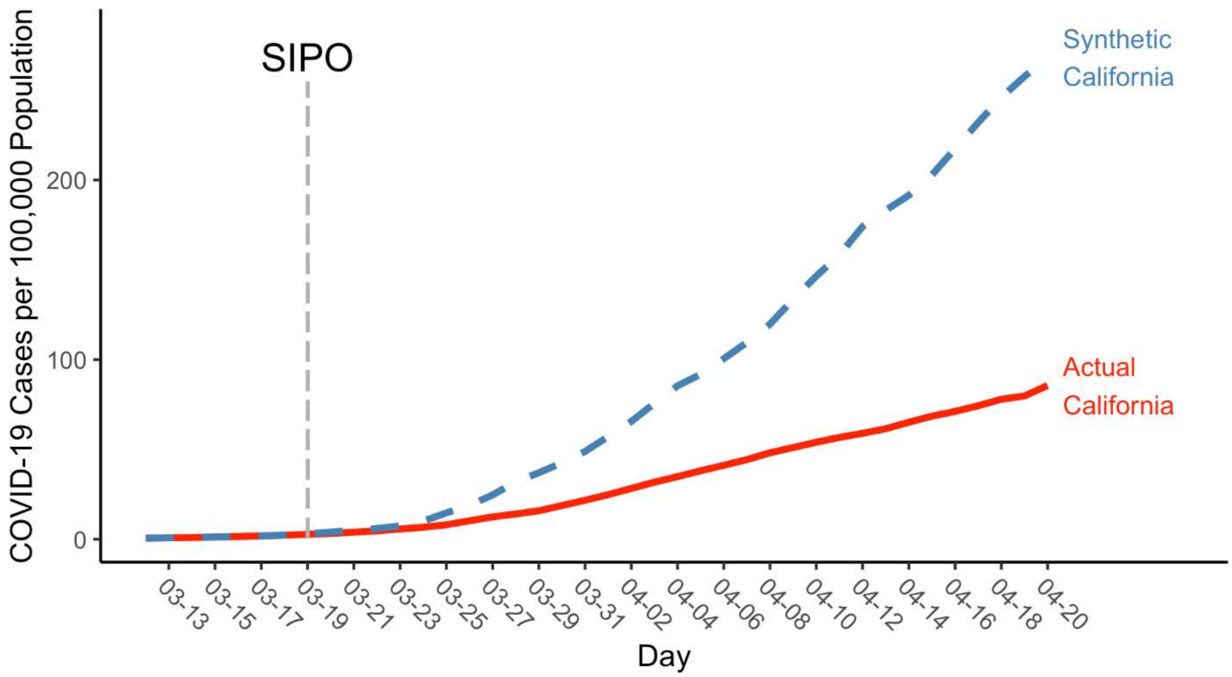
Notes: Estimate is generated using synthetic control methods. The matching was based on seven days of pre-SIPO COVID-19 cases per 100,000. March 28 is the 5th day (median incubation period) after the first treatment date for donor state. The donor states shaded in Figure 5b are those that received a weight of at least .015 in the estimation of the synthetic control counterfactual for California. Darker shaded states received more weight. Synthetic California is comprised of SD (.177), MA (.148), CO (.106), ME (.096), DC (.029), NE (.017), WY (.017), and RI (.016). In addition, 30 states each contributed a weight between .010 and .015.

Appendix Figure 6: Synthetic Control Estimates for Cases Per 100,000
Limited Post-Treatment Window Between March 12 and April 3
[Matching Variables: COVID-19 Cases on All Pre-Treatment Days]



Notes: Estimate is generated using synthetic control methods. The matching was based on seven days of pre-SIPO COVID-19 cases per 100,000. April 4 is the 12th day (median incubation period) after the first treatment date for donor state. The donor states shaded in Figure 5b are those that received a weight of at least .015 in the estimation of the synthetic control counterfactual for California. Darker shaded states received more weight. Synthetic California is comprised of SD (.177), MA (.148), CO (.106), ME (.096), DC (.029), NE (.017), WY (.017), and RI (.016). In addition, 30 states each contributed a weight between .010 and .015.

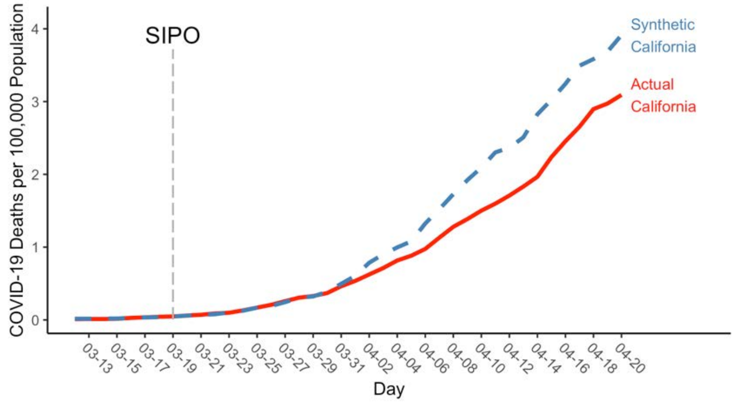
Appendix Figure 7: Synthetic Control Estimates for Cases Per 100,000 Using Only Later Adopters (April 6 or Later) or Non-Adopters as Donor States [Matching Variables: COVID-19 Cases on All Pre-Treatment Days]



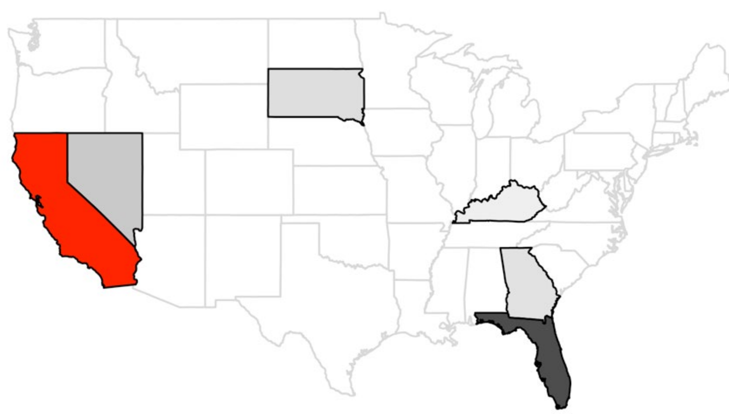
Notes: Estimate is generated using synthetic control methods. The matching was based on seven days of pre-SIPO COVID-19 cases per 100,000. The donor states are restricted to states that never adopted a SIPO or states that have 4 or fewer days of post-treatment data.

Appendix Figure 8: Synthetic Control Estimates for Deaths Per 100,000
Forced Match on Deaths Through Incubation and First Symptoms Until ARDS
[Matching Variables: COVID-19 Cases on 3 Pre-Treatment & 3 Post-Treatment Days & Urbanicity]

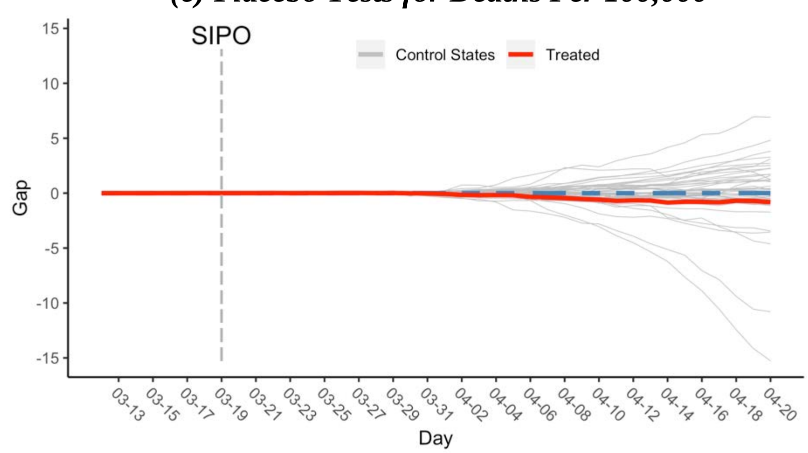
(a) Synthetic California v. Actual California Deaths Per 100,000



(b) Donor States for Synthetic California Deaths

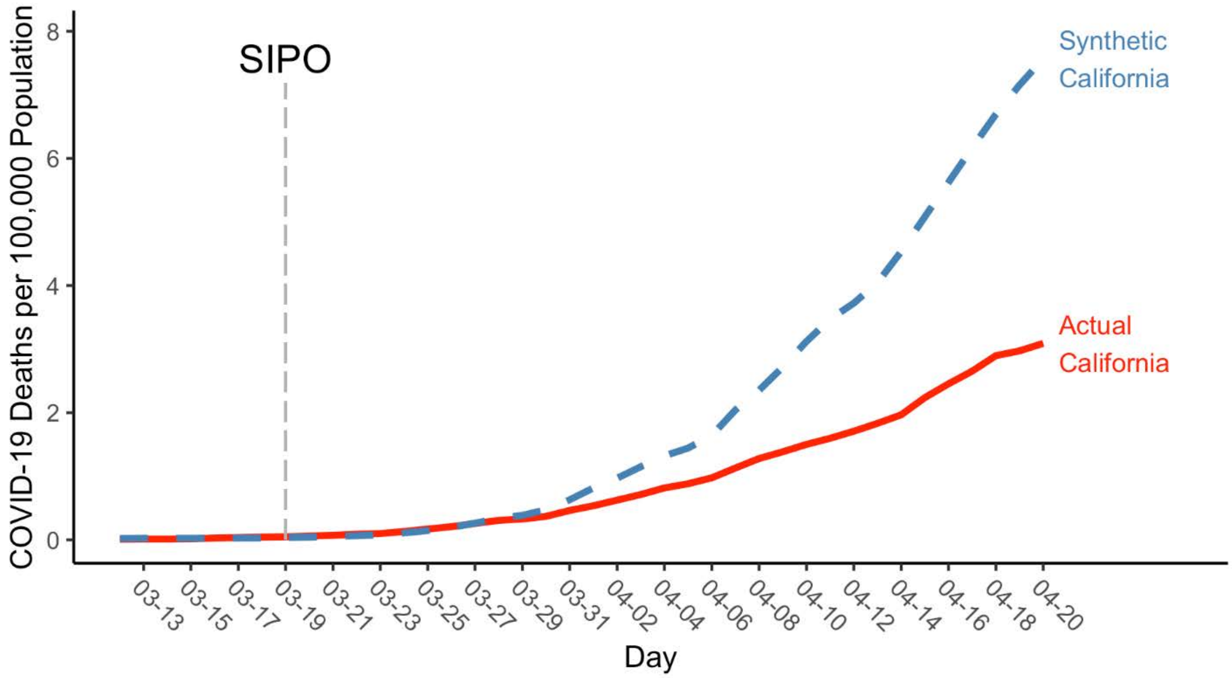


(c) Placebo Tests for Deaths Per 100,000



Notes: Estimate is generated using synthetic control methods. The matching was based on seven days of pre-SIPO COVID-19 testing per 100,000. The donor states shaded in Appendix Figure 8b are those that received a weight of at least .015 in the estimation of the synthetic control counterfactual for California. Darker shaded states received more weight. Synthetic California is comprised of FL (.559), NV (.172), SD (.095), GA (.082), HI (.058), and KY (.033).

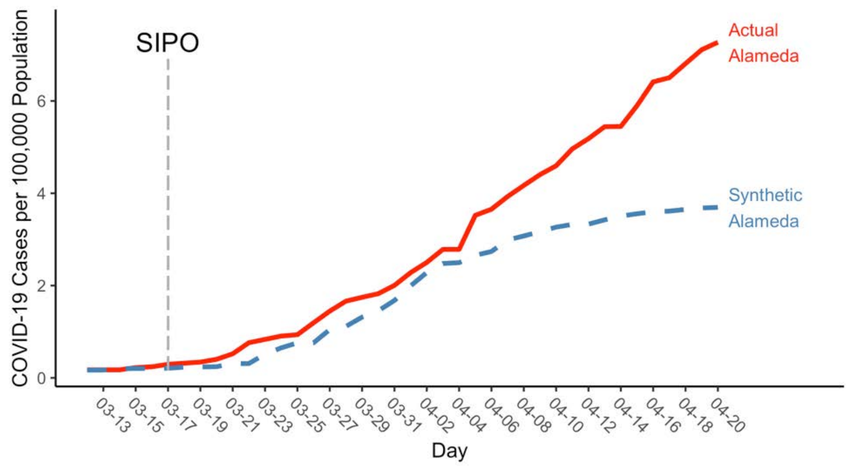
Appendix Figure 9: Synthetic Control Estimates for Deaths Per 100,000
[Matching Variables: COVID-19 Cases on All Pre-Treatment Days]



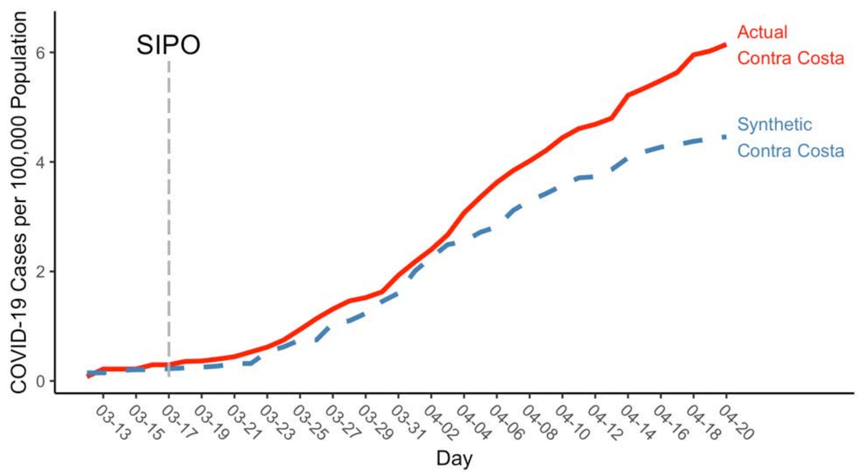
Notes: Estimate is generated using synthetic control methods. The matching was based on seven days of pre-SIPO COVID-19 cases per 100,000. The donor states shaded in Figure 5b are those that received a weight of at least .015 in the estimation of the synthetic control counterfactual for California. Darker shaded states received more weight. Synthetic California is comprised of SD (.177), MA (.148), CO (.106), ME (.096), DC (.029), NE (.017), WY (.017), and RI (.016). In addition, 30 states each contributed a weight between .010 and .015.

Appendix Figure 10: Synthetic Control Method for County SIPO [Matching Variables: COVID-19 Cases on All Pre-Treatment Days]

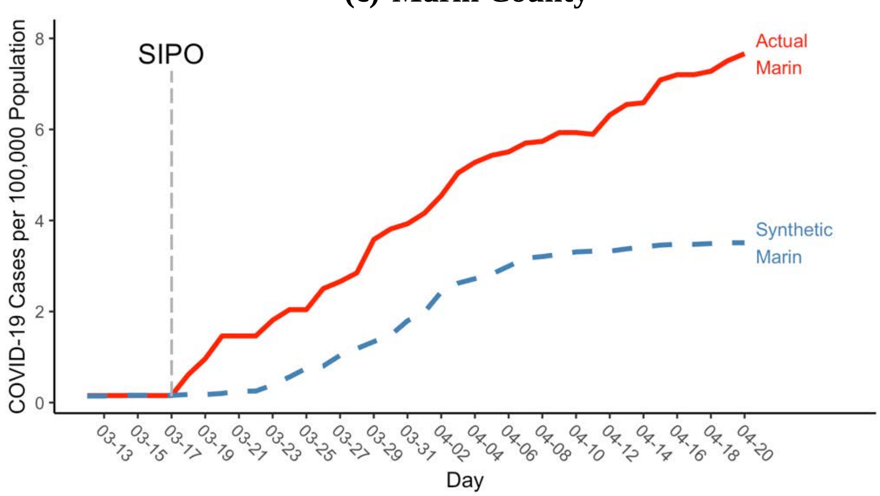
(a) Alameda County



(b) Contra Costa County

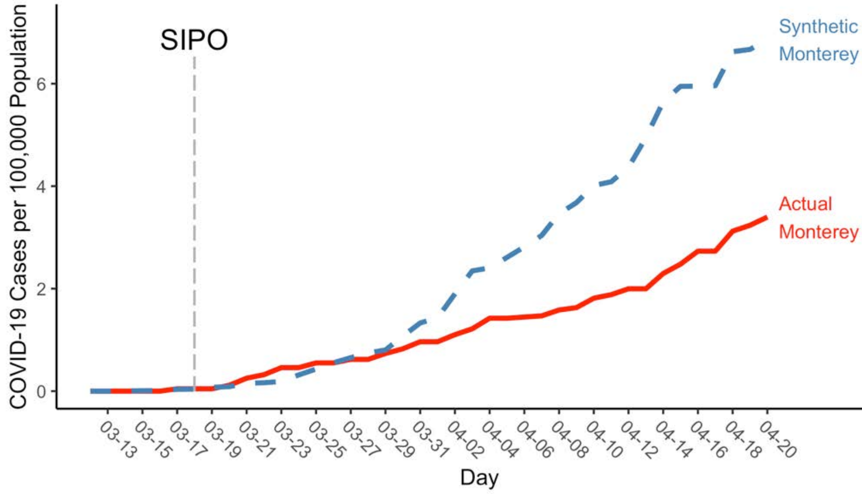


(c) Marin County

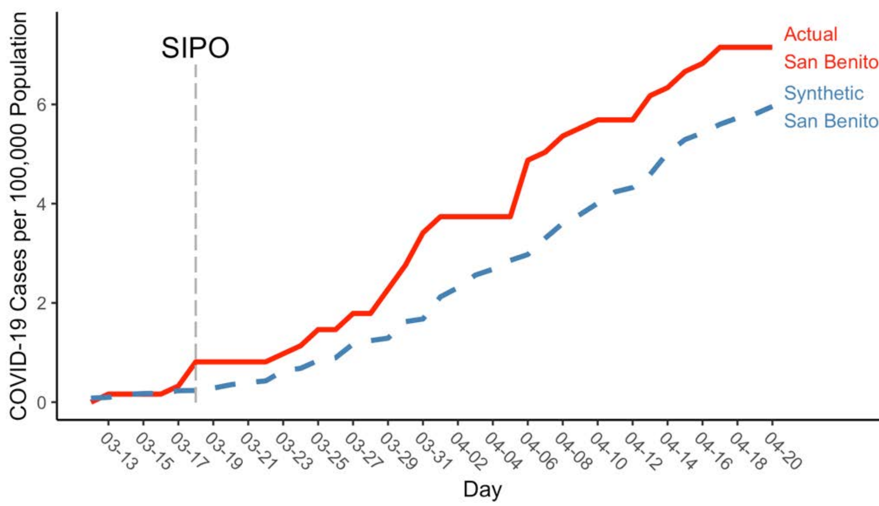


Appendix Figure 10 Continued

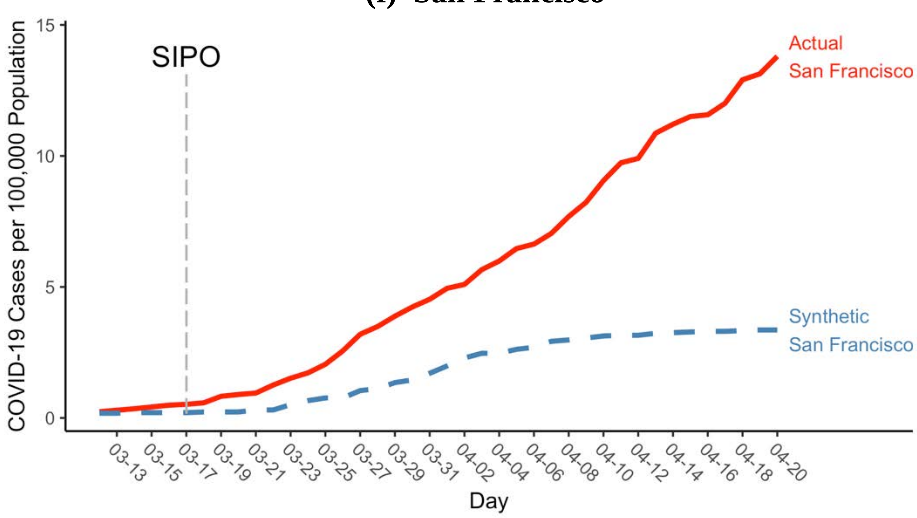
(d) Monterey County



(e) San Benito County

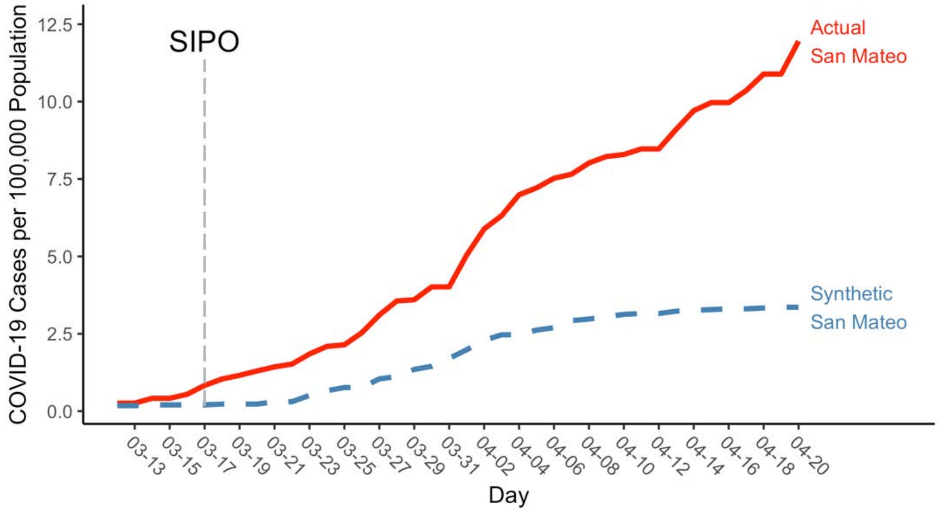


(f) San Francisco

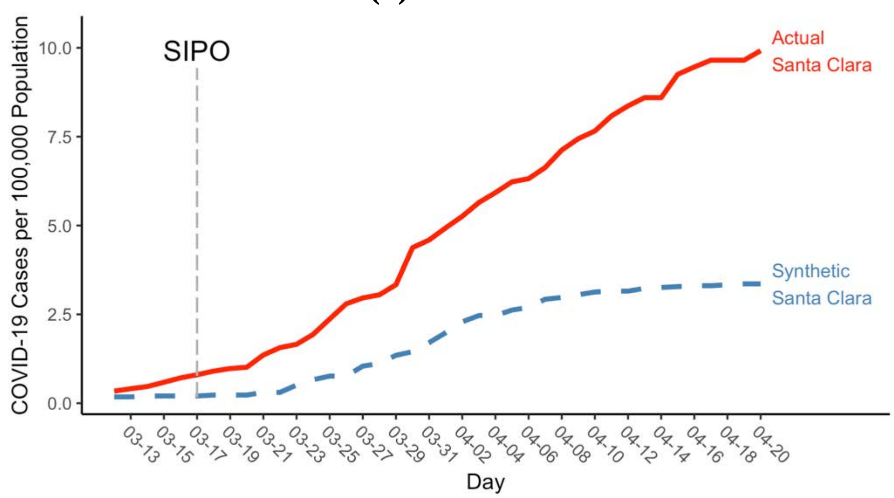


Appendix Figure 10 Continued

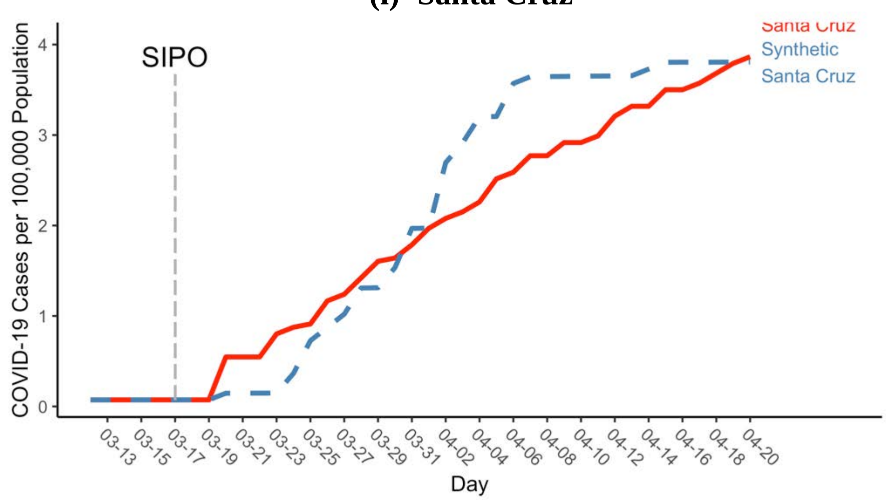
(g) San Mateo



(h) Santa Clara

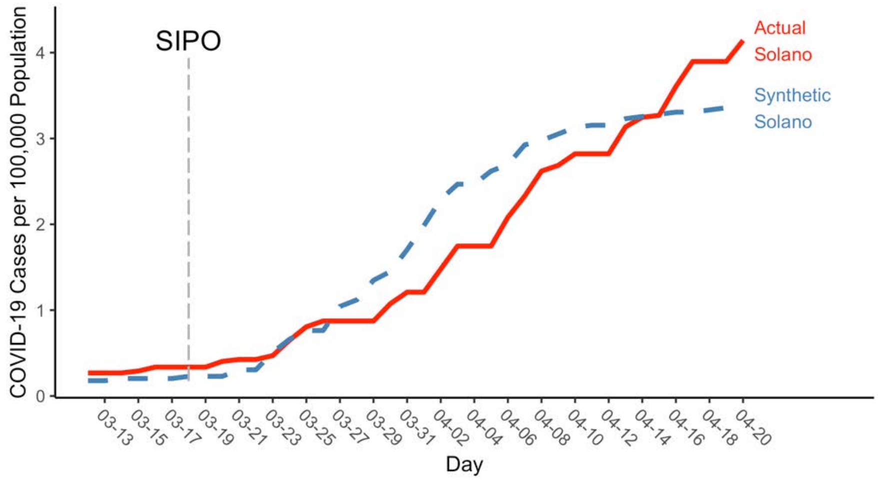


(i) Santa Cruz

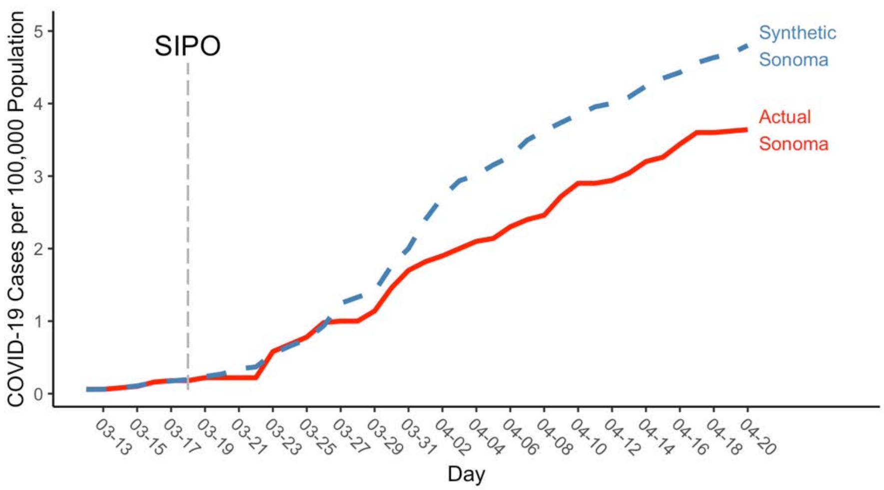


Appendix Figure 10 Continued

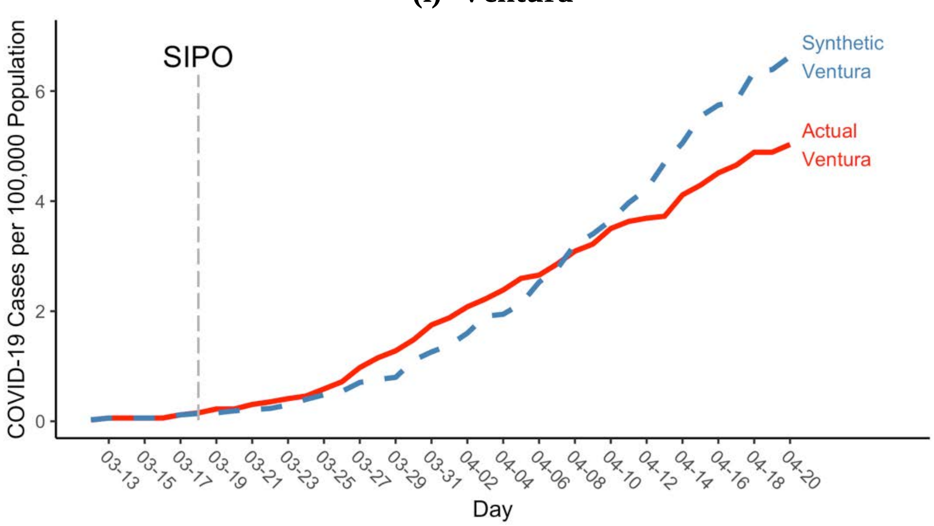
(j) Solano



(k) Sonoma

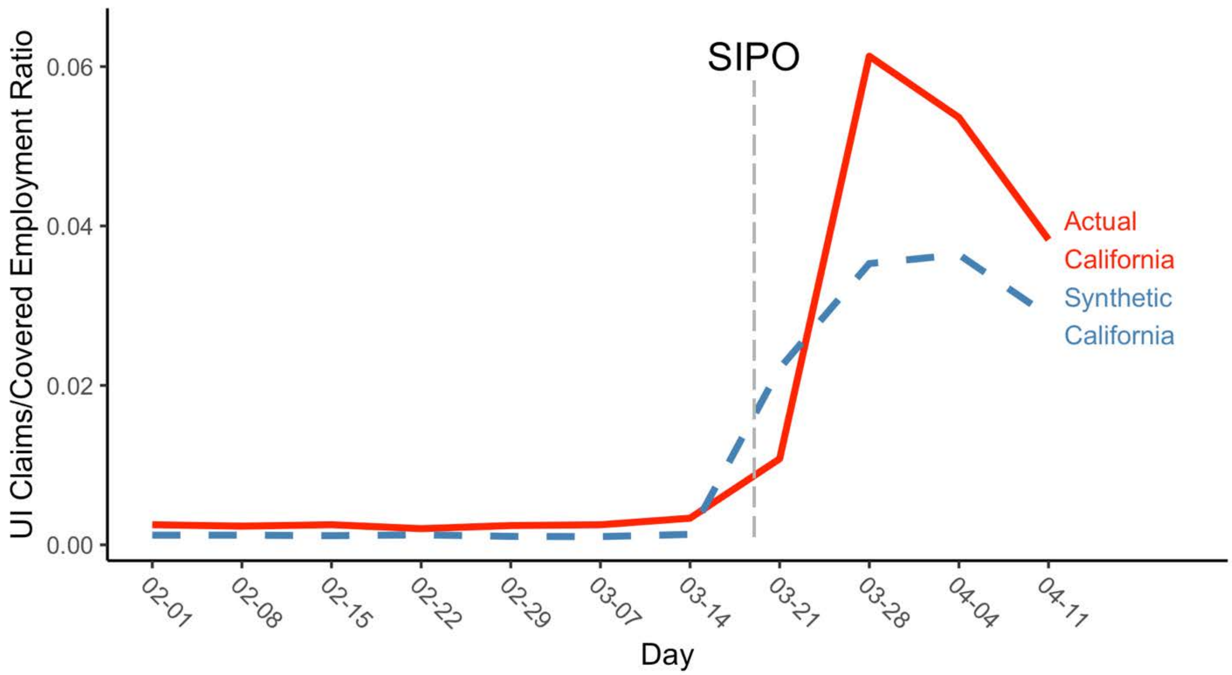


(l) Ventura



Notes: Estimate is generated using synthetic control methods. The matching was based on seven days of pre-SIPO COVID-19 cases per 100,000.

Appendix Figure 11: Synthetic Control Estimates for UI Jobless Claims Rate [Matching Variables: COVID-19 Cases in Pre-Treatment Period]



Notes: Estimate is generated using synthetic control methods. Synthetic California generated using the synthetic weights from column (1) of Table 1.

Appendix Table 1: SIPO Effective Dates, March 19-April 9, 2020

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.

Appendix Table 2: Synthetic Control Estimates of the Relationship between California SIPO and COVID-19 Cases and Deaths, Using All States, Never Adopters, or Never or Late Adopters

	Donors: *All 50 States*	Donors: *Never Adopters*	Donors: *Never or Late Adopters*
	(1)	(2)	(3)
		Panel I: Cases per 100,000	
SIPO	-42.751***	-65.646	-65.06
P-Value	[0.039]	[0.182]	[0.231]
One Sided P-Value	[0.039]	[0.182]	[0.231]
		Panel II: Deaths per 100,000	
SIPO	-3.756	-0.079	-0.073
P-Value	[0.200]	[1.000]	[1.000]
One Sided P-Value	[0.100]	[0.273]	[0.231]

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

Notes: Estimate is generated using synthetic control methods. The matching was based of the pre-SIPO covid-19 cases per 100,000. Note that in column (2), synthetic California is comprised of MA (.38), OK (.22), UT (.22), ND (.14), and WY (.03). In column (3), synthetic California is comprised of MA (.38), UT (.22), OK (.18), ND (.15), SC (.03), and WY (0.03).

Appendix Table 3: Covariate Match for Synthetic Controls

	CA (1)	Rest of US (2)	Synthetic CA (3)
	Panel I: Urbanicity Match (Case)		
Urbanicity	95.00	73.69	83.04
	Panel II: Urbanicity and Population Density Match (Case)		
Urbanicity	95.00	73.69	92.32
Density	253.93	427.61	857.03
	Panel III: Testing Match (Case)		
Testing Rate	133.94	212.13	222.90
	Panel IV: Policy Match (Case)		
Travel Ban	0.00	0.14	0.39
Disaster	0.62	0.27	0.34
	Panel V: Urbanicity Match (Death)		
Urbanicity	95.00	73.69	91.16
	Panel VI: Urbanicity and Population Density Match (Death)		
Urbanicity	95.00	73.69	91.23
Density	253.93	427.61	247.28
	Panel VII: Policy Match (Death)		
Testing Rate	133.94	212.13	195.14
	Panel VIII: Policy Match (Death)		
Travel Ban	0.00	0.14	0.03
Disaster	0.62	0.27	0.15

Appendix Table 4: Estimated Average Cases/ per 100,000 in the Post-SIPO Period: Excluding HI & AL

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel I: Cases per 100,000			
SIPO	-43.291**	-50.264**	-43.351**	-61.257**	-23.861*	-85.286*
P-Value	[0.024]	[0.048]	[0.071]	[0.048]	[0.238]	[0.071]
One Sided P-Value	[0.024]	[0.048]	[0.048]	[0.048]	[0.095]	[0.071]
			Panel II: Deaths per 100,000			
SIPO	-1.403	-1.302*	-1.341	-0.627	-1.424	-0.63
P-Value	[0.854]	[0.756]	[0.829]	[0.951]	[0.878]	[0.878]
One Sided P-Value	[0.220]	[0.098]	[0.366]	[0.366]	[0.341]	[0.146]
Observable used to construct the weights						
Pre-SIPO covid-19 Days	7	3	3	3	3	3
Urbanicity	No	Yes	Yes	No	Yes	No
Population Density	No	No	Yes	No	No	No
Testing Rates	No	No	No	Yes	Yes	No
Travel Restriction	No	No	No	No	Yes	No
Disaster Emergency	No	No	No	No	Yes	No
Shelter in Place Index	No	No	No	No	Yes	Yes

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

Notes: Estimate is generated using synthetic control methods. The number of donor states are 43. The matching was based of the pre-SIPO covid-19 cases per 100,000 and variables listed under each column.

Appendix Table 5: Covariate Match Between California, Never Adopters, and Never or Late Adopters

	(1)	(2)	(3)	(4)	(5)
	CA	Never Adopters	Synthetic CA Generated from Never Adopters	Never or Late Adopters	Synthetic CA Generated from Never or Late Adopters
Urbanicity	95.000	73.690	58.193	68.217	80.300
Testing Per 100,000 Pop	133.937	212.132	122.660	180.626	275.523
Density	253.931	427.690	100.800	126.700	360.52
Travel Ban	0.000	0.143	0.270	0.157	0.296
Disaster	0.615	0.268	0.347	0.247	0.237

Appendix Table 6: Local CA SIPO Effective Dates

Location	Date
Alameda County	March 17
Berkeley City	March 17
Contra Costa County	March 17
Marin County	March 17
Monterey County	March 18
San Benito County	March 18
San Francisco County	March 17
San Mateo County	March 17
Santa Clara County	March 17
Santa Cruz County	March 17
Solano County	March 18
Sonoma County	March 18
Ventura County	March 18

Sources: Compiled by the authors using the National Association of Counties and the authors own searches of county public health department websites.