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Effects of statewide stay-at-home orders on COVID-19 cases and deaths in the central USA

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Abstract

Purpose – This study seeks to determine the effects of stay-at-home orders in Spring 2020 on COVID-19 cases and deaths in the Central USA by comparing counties and health service areas that were and that were not subject to statewide orders.

Design/methodology/approach – This study estimates the effects of statewide stay-at-home orders on new COVID-19 cases and deaths within 19 central states, of which 14 had stay-at-home orders. It uses synthetic control analysis and nearest neighbor matching to estimate the effects at two geographic levels: counties and health service areas.

Findings – Statewide stay-at-home orders significantly reduced the number of new COVID-19 cases in the Central USA starting about three weeks after their effective dates; during the fourth week after their effective dates, the orders reduced the number of new cases per capita by 31%–57%. Statewide stay-at-home orders did not reduce the number of new COVID-19 deaths in the Central USA.

Social implications – The main purpose of stay-at-home orders in Spring 2020 was to "flatten the curve" so that hospitalizations would not exceed capacity. It is likely that stay-at-home orders in the Central USA reduced hospitalizations to some extent, although the effect on hospitalizations was likely smaller than the effect on cases.

Originality/value – This is the first study of stay-at-home orders in the USA to limit the population to a group of interior states. All coastal states had statewide stay-at-home orders and comparing coastal states with orders to interior states without them may be problematic.

Keywords COVID-19, Coronavirus, Stay-at-home orders, USA

Paper type Research paper

Introduction

All 50 states in the USA imposed various restrictions during the first few months of the coronavirus pandemic. Although there was variation in timing, almost all states imposed the same main restrictions. All 50 states closed K-12 public schools. Forty-nine states (all except South Dakota) closed restaurant dining rooms. Forty-nine states (again, all except South Dakota) prohibited large gatherings. And forty-five states (all except Arkansas, Nebraska, South Dakota, Utah and Wyoming) required nonessential businesses to close [1]. Of the major restrictions that were imposed, the one that states generally imposed last and lifted first and that had the greatest variation across states was the stay-at-home order. Still, 42 states imposed stay-at-home orders, while only eight did not. Within the Central USA – the 20 states located in the four Census divisions that include the word "Central" – there was greater variation in stay-at-home orders, as 14 states imposed them during the first few months of the pandemic, while six states did not.

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Because all states imposed most of the same restrictions during the first few months of the pandemic, it is difficult to determine how effective stay-at-home orders were in limiting the initial spread of the pandemic. The research has followed two basic approaches. The first approach estimates the effectiveness of the orders based on differences in COVID-19 case or death growth rates within states or counties before and after restrictions were adopted [2–7]. However, many other factors changed over time that may also have affected cases or deaths during those first few months, such as other restrictions, the availability of tests, knowledge about the virus and weather. Thus, it is difficult to accurately estimate the effects of restrictions based on differences in growth rates within areas over time.

The second approach estimates the effect of the orders based on differences in cases or deaths across states or counties that imposed and that did not impose the orders [8–12]. This approach may be preferable, because it is easier to control for differences across areas in factors that may have affected cases and deaths than it is to control for differences over time in those factors. However, it may be necessary to use the first approach to estimate the effects of stay-at-home orders in coastal states, because the eight interior states that never adopted those orders are likely poor controls for most coastal states.

This study seeks to determine the effects of stay-at-home orders on reported COVID-19 cases and deaths in 19 central states by comparing counties and health service areas (HSAs, which are groups of counties that people travel among for routine medical care) that were subject to statewide stay-at-home orders with counties and HSAs that were not.

Methodology

Data

Information on statewide stay-at-home orders was collected directly from state government websites. Table 1 shows when statewide orders were imposed and lifted in the 20 central

State	First full day of stay-at-home order	Last full day of stay-at-home order	Duration of stay-at-home order
Alabama	April 5	April 30	26 days
Arkansas	–	–	–
Illinois	March 22	May 29	69 days
Indiana	March 25	May 3	40 days
Iowa	–	–	–
Kansas	March 29	April 30	33 days
Kentucky	March 27	May 10	45 days
Louisiana	March 24	May 14	52 days
Michigan	March 24	June 1	70 days
Minnesota	March 28	May 17	51 days
Mississippi	April 4	April 27	24 days
Missouri	April 4	May 3	30 days
Nebraska	–	–	–
North Dakota	–	–	–
Ohio	March 24	May 19	57 days
Oklahoma	–	–	–
South Dakota	–	–	–
Tennessee	April 3	April 30	28 days
Texas	April 1	April 30	30 days
Wisconsin	March 25	May 13	50 days

Table 1. Timing of statewide stay-at-home orders in the Central USA

states. In some states, individual counties or cities had orders that started earlier or ended later than the statewide orders. However, because this study seeks to estimate the effects of the statewide orders, the starting and ending dates of the statewide orders are used. The six central states without date information in Table 1 did not adopt statewide orders. Although Oklahoma never adopted a statewide order, Oklahoma City, Tulsa and several other cities in Oklahoma did adopt orders, so that about half of Oklahoma's population was subject to a stay-at-home order during the first few months of the pandemic. Therefore, Oklahoma was excluded from the analyses, as even individual counties in Oklahoma were sometimes partly subject and partly not subject to stay-at-home orders.

County-level data on confirmed or probable COVID-19 cases and deaths were obtained from the New York Times website [13]. And county-level data on the demographic predictor variables were obtained from various U.S. Census Bureau and U.S. Department of Agriculture datasets [14, 15]; all covariates were measured in 2018. Table 2 shows descriptive statistics for the dependent variables and predictor variables used in any of the analyses. Some HSAs include counties in different states; if an HSA includes counties both in a treated state and in a control state, that HSA was divided into two HSAs for the analyses.

Table 2 shows some important differences between the counties and HSAs that were and that were not subject to statewide stay-at-home orders. In particular, the treated counties and HSAs had more COVID-19 deaths per capita; larger, denser, more urban, younger and more diverse populations (although a smaller percentage of Native Americans); higher poverty rates and unemployment rates; and less negative domestic migration rates (meaning that fewer people were relocating away from the treated counties and HSAs to other states). Therefore, it is important to match the treated units and control units carefully.

Analytical methods

At each geographic level, linear regressions were used first to identify the demographic variables that were significant predictors of COVID-19 cases or deaths at that level, using data from March 2020 through June 2020. Twenty-three different demographic variables were considered in those regressions and 10 were used for cases at the county level, 11 were used for deaths at the county level, 11 were used for cases at the HSA level and 8 were used for deaths at the HSA level.

Synthetic control analysis was then used to match treated units with synthetic control units on the predictor variables, including a pretreatment value of the dependent variable averaged over the 7 days prior to the effective date of the stay-at-home order. Synthetic control analysis constructs a synthetic control unit for each treated unit by finding a weighted combination of control units that matches the treated unit as closely as possible on the pretreatment averages of the predictor variables. An advantage to synthetic control analysis is that a weighted combination of control units can provide a better match for a treated unit than any individual control unit or even than an average of two or more control units. However, unlike with the nearest neighbor matching that is described below, the synthetic control analysis did not adjust for any remaining bias due to differences in predictor variable averages between the treated units and their synthetic control units. Also, synthetic control analysis works best when the units have a significant history of pretreatment data available for the dependent variable [16]. Almost one-half of counties and one-quarter of HSAs had no cases during the week before their stay-at-home orders took effect and about 90% of counties and three-quarters of HSAs had no deaths during that period. So, many treated units did not have a meaningful pretreatment dependent variable average for matching, which may have affected the results, although this study partly addressed that issue by including other covariates that are important predictors of the dependent variable.

Table 2. Descriptive statistics

Variable	Central states with stay-at-home orders County-level mean	County-level SD	HSA-level mean	HSA-level SD	Central states without stay-at-home orders County-level mean	County-level SD	HSA-level mean	HSA-level SD
Dependent variables								
Average new cases per 100,000 people 22–28 days after stay-at-home order	5.6	38.7	5.0	12.0	5.7	29.2	7.0	20.4
Average new deaths per 100,000 people 22–28 days after stay-at-home order	0.2	0.5	0.2	0.4	0.08	0.47	0.09	0.29
Lagged dependent variables								
Average new cases per 100,000 people 1–7 days before stay-at-home order	1.1	2.1	1.2	2.2	0.9	2.2	1.0	1.4
Average new deaths per 100,000 people 1–7 days before stay-at-home order	0.03	0.18	0.04	0.20	0.01	0.13	0.02	0.09
Other predictor variables (measured in 2018)								
Population (000s)	80.0	25.5	300.0	660.8	25.2	55.7	95.1	157.5
Population density	143.1	379.8	125.8	225.3	39.8	117.0	33.1	39.4
Land area	670.2	442.3	2,545.2	2,284.9	853.7	554.2	3,203.1	2,715.8
Rural/urban code	5.1	2.6	4.6	2.1	6.7	2.3	6.1	1.8
Median household income (000s)	50.8	11.9	51.2	9.9	52.6	10.1	52.5	8.8
Poverty rate	15.6	6.2	15.7	5.2	13.8	6.5	14.1	5.2
Unemployment rate	4.2	1.4	4.1	1.1	3.1	1.1	3.2	1.1
Median age	39.9	4.5	38.8	3.9	42.1	5.6	40.5	4.2
% of residents who were older than 17	76.2	2.9	76.0	2.5	76.3	3.4	76.3	2.3
% of residents who were older than 84	2.1	0.8	2.1	0.7	3.0	1.2	2.8	0.9
% of residents who were Asian	0.8	1.2	1.1	1.2	0.6	0.9	0.8	0.7
% of residents who were black	8.6	14.5	9.7	13.3	3.6	9.9	4.9	11.3
% of residents who were Hispanic	8.6	15.3	9.2	15.5	3.7	5.0	4.6	4.5
% of residents who were native American	0.8	3.0	0.7	1.5	3.9	13.5	3.6	9.2
% of residents with high school diploma or less	50.3	10.1	47.7	8.4	45.2	8.2	44.5	7.4
% of residents with bachelor's degree or more	19.5	8.0	21.7	7.1	21.1	6.6	22.2	6.3
Domestic migration rate	−0.8	10.8	−1.6	8.6	−4.4	11.0	−4.4	8.9
International migration rate	0.8	1.5	1.0	1.1	1.3	2.8	1.6	2.5
N	1,426		381		386		104	

Nearest neighbor matching was also used to match treated units and control units on the predictor variables. Nearest neighbor matching imputes the missing counterfactual value of the dependent variable for each unit using an average of the dependent variable values of similar units from the other group. Synthetic control estimators and nearest neighbor estimators may each exhibit a different type of bias [17], so it can be useful to compare estimates from both models. Each HSA and county were matched with the three nearest neighbors in the other group within a caliper of 10. Units that did not have three neighbors within a caliper of 10 in the other group were excluded. A bias adjustment was used in the nearest neighbor matching analyses, which adjusts the difference in the dependent variable values between matched units to account for differences in the values of their predictor variables. And heteroscedasticity robust standard errors were used.

Ethical considerations

This study used only publicly available, nonidentifiable data and thus did not require human subjects review.

Results

Synthetic control analysis

Table 3 shows the synthetic control estimates of the effects of stay-at-home orders on the 7-day average of new cases or deaths per 100,000 people at each geographic level for the first 42 days after the effective date of those orders. The treated counties and HSAs had significantly more new cases per capita for the first 16 days of their statewide stay-at-home orders and significantly more new deaths per capita for the first 19–23 days; the states that imposed orders likely anticipated those increases when they imposed their orders. After that initial period, there was never a significant effect on new deaths per capita. The treated counties and HSAs had significantly fewer new cases per capita starting 23–25 days after the effective date of their orders.

Table 1 shows that the length of statewide stay-at-home orders in the central states ranged from 24 days to 70 days. Also, some central states started to relax other restrictions on May 1, which was 26 days after the last statewide stay-at-home order in the central states was imposed. Therefore, the synthetic control estimates of the effects of stay-at-home orders after about four weeks likely are contaminated by the effects of some central states relaxing those orders or other restrictions. For that reason, this study focuses on the effects during the fourth week after the effective date of the stay-at-home orders. During the 7-day period ending 28 days after the effective date of the orders, treated counties had 2.90 fewer new daily cases per 100,000 people than their synthetic control units, which represents a 38% reduction, and treated HSAs had 6.27 fewer new daily cases per 100,000 people than their synthetic control units, which represents a 57% reduction. The county-level effect was significant at the 5% level and the HSA-level effect was significant at the 1% level.

Nearest neighbor matching

Table 4 presents the results of the nearest neighbor matching analysis. During the 7-day period ending 28 days after the effective date of the stay-at-home orders, treated counties had 2.51 fewer new daily cases per 100,000 people than control counties, which represents a 31% reduction, and treated HSAs had 3.60 fewer new daily cases per 100,000 people than control HSAs, which represents a 42% reduction. The effect at the county level was significant at the 5% level, but the effect at the HSA level was not quite significant, with a p-value of 0.11. As with the synthetic control analysis, the effect on deaths per 100,000 people in the nearest neighbor matching analysis was not nearly significant during the 7-day period ending 28 days after the effective date of the stay-at-home orders at either geographic level.

Days after start of stay-at-home order	County-level effect on 7-day average of New confirmed or probable COVID-19 cases per 100,000 people[a]	New confirmed or probable COVID-19 deaths per 100,000 people[a]	HSA-level effect on 7-day average of New confirmed or probable COVID-19 cases per 100,000 people[b]	New confirmed or probable COVID-19 deaths per 100,000 people[b]
1	0.11	0.01†	0.26†	0.03
2	0.14	0.01†	0.32*	0.03
3	0.17	0.01*	0.27	0.04
4	0.26	0.02**	0.44***	0.04
5	0.31	0.03**	0.55***	0.05
6	0.26	0.02**	0.60***	0.05
7	0.31	0.03**	0.64**	0.05
8	0.58**	0.02*	0.78***	0.05
9	0.66**	0.02*	0.88***	0.04**
10	0.89***	0.03	1.18***	0.05***
11	1.01***	0.02	1.27***	0.05***
12	1.28***	0.03	1.42***	0.06***
13	1.33***	0.04	1.57**	0.07***
14	1.51***	0.05	1.67*	0.07***
15	1.41**	0.07	1.69**	0.09***
16	1.43**	0.08	1.66†	0.11*
17	1.00	0.09*	1.33	0.11***
18	0.42	0.11*	1.13	0.13*
19	−0.14	0.11*	0.91	0.13*
20	−0.54	0.11	0.62	0.13*
21	−1.25	0.12	0.30	0.13*
22	−1.37	0.12	0.14	0.13**
23	−1.98†	0.12	−0.94	0.14*
24	−2.05†	0.12	−1.59	0.13
25	−2.67**	0.10	−4.61**	0.12
26	−2.63**	0.10	−4.73***	0.12
27	−2.68**	0.11	−6.03***	0.13
28	−2.90**	0.11	−6.27***	0.12
29	−2.78**	0.08	−6.48***	0.11
30	−3.25***	0.08	−6.44***	0.10
31	−3.98*	0.07	−5.78***	0.12
32	−4.57***	0.07	−5.86***	0.12
33	−4.90***	0.05	−6.87***	0.12
34	−5.82***	0.04	−6.69***	0.13
35	−6.21***	0.04	−7.09**	0.13
36	−7.46***	0.05	−7.57**	0.14
37	−7.56***	0.05	−8.27*	0.12
38	−8.44***	0.04	−14.09†	0.09
39	−7.49***	0.05	−12.23†	0.09
40	−7.10***	0.03	−11.20*	0.08
41	−6.69***	0.01	−11.44*	0.07
42	−6.05**	−0.01	−11.34	0.07

Note(s): ***p < 0.001; **p < 0.01; *p < 0.05; †p < 0.10; [a] N = 1,426 treated counties and 386 possible control counties; [b] N = 381 treated HSAs and 104 possible control HSAs

Table 3. Synthetic control estimates of the effect of statewide stay-at-home orders in Spring 2020 on COVID-19 cases and deaths in the Central USA

Discussion

Although this study uses a different population and different methods than other studies of the effects of stay-at-home orders in the USA, the results are consistent with the results from most other studies. Almost all other studies have also found that stay-at-home orders significantly decreased the number of new cases [3–5, 7, 12]. Fewer studies have considered deaths and the results of those studies have been less consistent, with one study finding significant effects on both cases and deaths [12], one study finding significant effects on cases but not on deaths [10] and one study finding no effects on cases or deaths [6].

Why might statewide stay-at-home orders in the Central USA have reduced the number of cases, but not the number of deaths? One possible explanation would be if the states with orders had tested less aggressively than the states without orders. In that case, the states with orders may simply have detected fewer less severe cases and may have underreported their cases to a greater extent than the control states. Two indicators of how aggressively a state tested are the number of tests per capita and the percentage of positive tests. States that tested less aggressively might have fewer tests per capita and a higher percentage of positive tests. According to data from the COVID Tracking Project [18], through March 3, 2020, the 14 central states with orders conducted 5% fewer tests per capita and had a 13% higher positive test rate than the five central states without orders. So, testing differences may explain part of the effect on cases found in this study, but they likely do not explain most of the 31%–57% effect on cases.

A second possible explanation would be if the states with orders had a greater percentage of people that were at risk of serious complications from COVID-19 because of age or preexisting medical conditions. The Kaiser Family Foundation calculated the percentage of at-risk adults in each state – people older than age 64 and other adults with certain preexisting conditions such as heart disease, chronic obstructive pulmonary disease, uncontrolled asthma, diabetes or a body mass index greater than 40 [19]. The overall percentages of at-risk adults are almost identical in the 14 central states with stay-at-home orders and the five central states without orders, so this factor does not help to explain why stay-at-home orders reduced the number of cases in the Central USA, but not the number of deaths.

A third possible explanation would be if a greater percentage of at-risk people became infected in the treated states than in the control states, even though the overall populations in the two groups have similar at-risk percentages. In particular, nursing facility residents comprised a large percentage of COVID-19 deaths in many states, especially during the first few months of the pandemic. So, if the central states with orders had a greater percentage of nursing facility deaths during the analysis period than the central states without orders, that could help to explain why stay-at-home orders did not reduce the number of deaths, although they reduced the number of cases. The Foundation for Research on Equal Opportunity calculated the percentage of COVID-19 deaths occurring in nursing and assisted-living facilities [20]. Among the 14 central states that had data available through May 12, 2020, the 11 states with stay-at-home orders had a lesser percentage of nursing facility deaths than the three states without orders, so this factor also does not help to explain why stay-at-home orders reduced the number of cases in the Central USA, but not the number of deaths.

Therefore, this study cannot fully explain why stay-at-home orders reduced the number of cases in the Central USA, but not the number of deaths. It may be that people who were at risk of serious complications stayed home in the states without orders, while younger and healthier people went out and became infected, increasing the number of cases without

Table 4. Nearest neighbor matching estimates of the effect of statewide stay-at-home orders in Spring 2020 on COVID-19 cases and deaths in the Central USA

Days after start of stay-at-home order	County-level effect on 7-day average of New confirmed or probable COVID-19 cases per 100,000 people[a]	County-level effect on 7-day average of New confirmed or probable COVID-19 deaths per 100,000 people[b]	HSA-level effect on 7-day average of New confirmed or probable COVID-19 cases per 100,000 people[c]	HSA-level effect on 7-day average of New confirmed or probable COVID-19 deaths per 100,000 people[d]
28	−2.51*	0.07	−3.60	0.05

Note(s): *$p < 0.05$; [a] N = 1,419 treated counties and 386 control counties; [b] N = 1,402 treated counties and 386 control counties; [c] N = 364 treated HSAs and 104 control HSAs; [d] N = 367 treated HSAs and 104 control HSAs increasing the number of deaths. Of course, it is also possible that other variables that were not controlled for in this study help to explain this result. Apart from the stay-at-home orders, the 19 central states generally adopted the same major restrictions, such as closing schools, nonessential businesses and restaurant dining rooms and prohibiting gatherings of more than ten people. However, as noted above, a few central states that did not adopt stay-at-home orders also did not adopt one or more of these other restrictions. Therefore, this study may overstate the effects of the stay-at-home orders by also including partial effects of those other restrictions. Other models were considered that controlled for the other major social distancing restrictions, but there was too little variation in those restrictions across states to estimate their effects reliably.

This study has some important limitations that were noted above. First, it is believed that COVID-19 cases were significantly underreported during the first few months of the pandemic, which may have affected this study's results; however, as was discussed above, testing differences across the central states do not explain most of the effects on cases found in this study. Second, the lack of a meaningful pretreatment history of cases or deaths for many of the counties and HSAs may have affected this study's synthetic control results; however, those results were similar to this study's nearest neighbor results and results from other studies of stay-at-home orders in the USA. Third, this study's estimates of the effects of stay-at-home orders may have included partial effects of other social distancing restrictions that this study was not able to control for and, as a result, this study may overstate the effects of the stay-at-home orders.

Conclusion

Stay-at-home orders in the USA during the first few months of the pandemic may have produced mixed results, with most research finding that they significantly reduced the number of cases, but not the number of deaths. This study makes an important addition to that research by being the first study to focus on a group of interior states. All states that did not adopt stay-at-home orders during the first few months of the pandemic were interior states, so limiting the treatment group also to interior states, as this study does, may be preferable, as it is difficult to fully control for all of the important differences between coastal states with stay-at-home orders and interior states without them. This study finds that stay-at-home orders in the Central USA may have reduced the number of cases per capita by 31%–57% by the fourth week after they were imposed, but likely did not affect the number of deaths per capita.

The main stated purpose of the restrictions imposed during the first few months of the pandemic, including the stay-at-home orders, was to "flatten the curve" so that hospitalizations would not exceed capacity, especially in terms of intensive care unit beds and respirators [21]. Unfortunately, county-level data on hospitalizations during the first few months of the pandemic are not available, so the effect of stay-at-home orders on hospitalizations in the Central USA cannot be determined. However, considering that hospitalizations are an intermediate outcome between cases and deaths, with about 10–20% of confirmed cases resulting in hospitalizations and about 10–20% of hospitalizations resulting in deaths during the first few months of the pandemic, it seems likely that the stay-at-home orders in the Central USA reduced hospitalizations to some extent, although the effect on hospitalizations was likely smaller than the effect on cases.

Conflict of Interest: None

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