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ORIGINAL ARTICLE

The Local and Aggregated Impacts of Stay-at-Home Orders on State Level Unemployment Outcomes

Allen Bellas[1] · Lea-Rachel Kosnik[2]

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Abstract
Initial research on the effect of pandemic related stay-at-home orders (SAHO) on subsequent US state unemployment rates found inconclusive results regarding the magnitude of the effect. This research helps to clarify the debate, finding that while own-state SAHOs affected unemployment outcomes, it was actually the *national* level of SAHO implementation across the country that had an even greater impact. While these results do not offer direct guidance on when or whether SAHOs should have been issued in any given state, they do help to clarify the impact of SAHOs on various measures of US unemployment.

Keywords COVID · Stay-at-home order · Unemployment · Health · Jobless claims

JEL Classification H7 · I1 · J6

Introduction

When COVID-19 hit the USA in early 2020, there was debate about the proper policy response to managing it (Greenstone and Nigam 2020; Thunstrom et al. 2020). By early April, however, the majority of states in the USA had decided to implement statewide stay-at-home orders (SAHO) in an effort to reduce infection rates and tame the pandemic. Such a policy response was not without projected costs, however, a primary one being the effect on business and employment.

Any given state-level SAHO would be expected to affect that state's economy, of course, but in an interconnected national economy like the USA, one would suspect that its impact would also be felt beyond a single state's borders, as both bilateral trade and supply chains are impacted. For example, in April 2020 meatpacking

✉ Allen Bellas
allen.bellas@metrostate.edu

1 College of Management, Metropolitan State University, Minneapolis, MN 55403, USA

2 Department of Economics, University of Missouri, St. Louis, USA

plants in a few states were closed due to COVID concerns, and these plant closures affected downstream meat-related industries across the country (USDA Economic Research Service 2021). Similarly, many states are dependent on inter-state trade for basic energy needs. Missouri, for example, imports the majority of its coal from Wyoming, and California imports a third of its electricity from nearby Pacific Northwest states. This paper investigates the effect of SAHOs not just within a state, but beyond its border to other states as well.

There is also the question as to whether SAHOs impacted different measures of unemployment differently, for example, lifting initial claims but not continuing claims or the broader unemployment rate in the same manner. By investigating the effect of SAHOs on different measures of unemployment – initial claims, continuing claims, and the overall unemployment rate – we seek an understanding of the nuanced effect of SAHOs on state-level unemployment measures. In particular, the CARES Act created an employee retention credit that incentivized employers to continue paying current employees who might otherwise have been laid off due to the COVID-19 outbreak, a policy likely to reduce initial claims for unemployment as current employees are retained, while perhaps reducing employment prospects for previously unemployed workers.

The USA entered uncharted territory in 2020 when responding to the coronavirus pandemic with state-level SAHOs. While the initial SAHOs were all lifted by the end of May, 2020 (see Table 1), debate continues as to their ultimate effect on the economy and joblessness. This paper asks: What effect did early 2020 SAHOs have, both directly on an issuing state, and aggregated across the country at the national level, on unemployment rates and unemployment insurance claims throughout the USA?

Literature Review

Early in the 2020 coronavirus pandemic a number of papers came out looking at the effects of the pandemic on unemployment in the USA. Bernstein et al. (2020), Cajner et al. (2020) and Coibion et al. (2020) all documented large initial spikes in unemployment in the first few months of the pandemic, particularly for low-wage workers. Petrosky-Nadeau et al. (2020) additionally assessed possible future paths for US unemployment into 2021 and predicted that while multiple paths were possible, it was most likely that unemployment would remain high for some time.

Montenovo et al. (2020), Alon et al. (2020) and Couch et al. (2020) produced early work looking at job losses in the USA in a disaggregated fashion, in particular the disparate effects on minorities and women due to their preponderance in low-wage sectors of the economy, and due to the effects of the pandemic on daycare and school closures. A main conclusion is that the COVID-19 pandemic has been particularly hard on minorities and women and that it is likely to aggravate inequality measures in the USA.

An interesting paper by Ceylan et al. (2020) took a historical perspective, comparing the coronavirus pandemic to previous global experiences with contagious diseases, including SARS (of 2002–2003), H5N1 (avian influenza of 2004–2006),

Table 1 initiation, end and length of stay at home orders (SAHO), by State

State	Initiation of SAHO	End of SAHO	Length of SAHO
California	19-March	4-May	46
Illinois	21-March	1-May	41
New Jersey	21-March	15-May	55
New York	22-March	15-May	54
Connecticut	23-March	20-May	58
Louisiana	23-March	15-May	53
Ohio	23-March	4-May	42
Oregon	23-March	15-May	53
Washington	23-March	31-May	69
Delaware	24-March	15-May	52
Indiana	24-March	1-May	38
Massachusetts	24-March	18-May	55
Michigan	24-March	11-May	48
New Mexico	24-March	16-May	53
West Virginia	24-March	4-May	41
Hawaii	25-March	7-May	43
Idaho	25-March	1-May	37
Vermont	25-March	6-May	42
Wisconsin	25-March	18-May	54
Colorado	26-March	27-May	62
Kentucky	26-March	11-May	46
Minnesota	27-March	18-May	52
New Hampshire	27-March	11-May	45
Alaska	28-March	24-April	27
Montana	28-March	26-April	29
Rhode Island	28-March	9-May	42
Kansas	30-March	4-May	35
Maryland	30-March	15-May	46
North Carolina	30-March	8-May	39
Virginia	30-March	14-May	45
Arizona	31-March	8-May	38
Tennessee	31-March	6-May	36
Nevada	1-April	9-May	38
Pennsylvania	1-April	8-May	37
Maine	2-April	1-May	29
Texas	2-April	1-May	29
Florida	3-April	4-May	31
Georgia	3-April	24-April	21
Mississippi	3-April	4-May	31
Alabama	4-April	30-April	26
Missouri	6-April	4-May	28
South Carolina	7-April	18-May	41

Table 1 (continued)

State	Initiation of SAHO	End of SAHO	Length of SAHO
Oklahoma	Varies by city		0
Utah	Varies by city		0
Wyoming	Varies by city		0
Arkansas			0
Iowa			0
Nebraska			0
North Dakota			0
South Dakota			0

and MERS (Middle East respiratory syndrome of 2012). An important conclusion from that paper is that such paradigm shifting events, similar to the shocks of war and political disruption, have enormous economic effects on multiple industries, in particular through the ripples of unemployment. As such, understanding the coronavirus' impact on unemployment is paramount for managing policy responses to these unprecedented socio-political shifts.

In line with this conclusion, Baek et al. (2020), Beland et al. (2020), Rojas et al. (2020), Forsythe et al. (2020), Kong and Prinz (2020), and Gupta et al. (2020) look not just at COVID-19 and unemployment, but at the intersection of the pandemic, unemployment, and related policy responses, such as state issued SAHOs and school closures.[1] Forsythe et al. (2020), Rojas et al. (2020), and Kong and Prinz (2020) all conclude that while the effects of the pandemic on unemployment were large, the policy response of state-wide SAHOs and other NPIs (non-pharmaceutical interventions) only modestly added to it. Baek et al. (2020) as well found that SAHOs contributed only a minority share to the initial rise in unemployment claims. In other words, the disruption in employment rates was driven by the health shock itself, not the subsequent policy responses.[2] Beland et al. (2020), however, find the opposite in a difference-in-difference framework that estimates the effects of SAHOs on labor market outcomes; their finding is that unemployment increased by nearly four percentage points for those states that implemented SAHOs. Gupta et al. (2020), as well, find that state policies were the main driver of subsequent unemployment rates, accounting for 60% of recorded shocks.

Obviously, the matter is not settled. Gaining a clearer picture of the effects of COVID-19 and state-based SAHOs on unemployment is important not just for a general understanding of the impacts of a pandemic, but for crafting responses on how to move forward. Research from other countries (Aum et al. 2020) also finds that the impact of lockdowns may be more nuanced than originally anticipated. If

[1] A similar paper that does this from a more international perspective is Aum et al. (2020).

[2] This resonates with the conclusion in Goolsbee and Syverson (2020), that finds that general economic activity declined due to the pandemic itself and individuals' response to it, more so than any state imposed policy.

the majority of SAHOs had only a modest effect on unemployment, then lifting them – or, reinstating second, and third wave versions of them – is not likely to have significant *additional* impacts on employment rates. If, however, SAHOs did in general have substantial effects on the labor market,[3] beyond the health effects of the pandemic itself, then how they are crafted and when they are implemented takes on greater weight (a point emphasized in Acemoglu et al. 2020).

Our paper adds to the existing literature in two ways. First, we examine the differential impacts of a state's own SAHO and SAHOs in other states on that state's unemployment. In a national economy with a high level of interstate commerce, it may well be that what is happening in other states is at least as important to a state's economy as what is happening in that state itself. Second, we examine different measures of unemployment (initial claims, continuing claims, and the overall unemployment rate), to determine the mechanism through which SAHOs impacted unemployment, especially in consideration of stimulus programs, such as the CARES act, meant to minimize the economic impact of the pandemic.

Methodology and Data

Data from several sources are used to construct a balanced longitudinal dataset with each of the fifty US states observed over thirty-six weeks from the beginning of December 2019 through August 2020. We use three different measures of unemployment, our dependent variable: the weekly number of initial claims for unemployment (*icu*), the number of continuing claims for unemployment (*ccu*), and the insured unemployment rate (*urate*). We test multiple measures in order to discern any heterogeneous effects of SAHOs on different aspects of unemployment.[4]

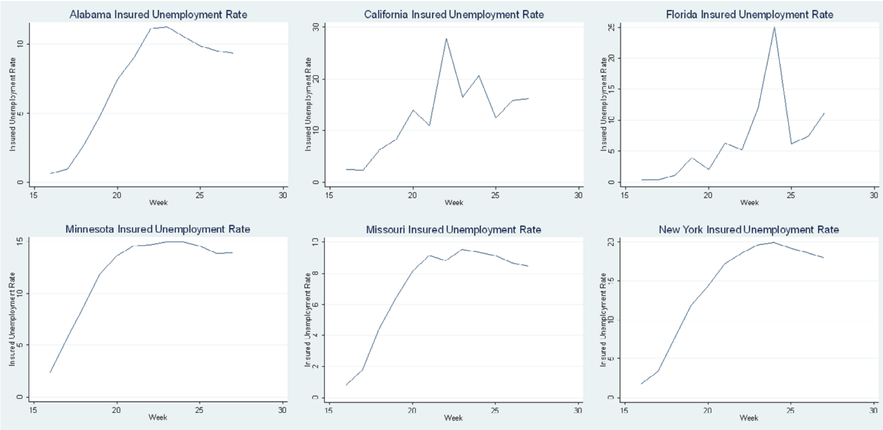
Individual states' experience with each of the different unemployment measures varied. Figures 1, 2, 3 show the dependent variables over time for six representative states (all fifty are available in an appendix from the authors upon request). It is clear that there is some heterogeneity in these measures both amongst themselves, and across different states. The three measures all come in the form of weekly claims data from the Department of Labor's Employment and Training Administration,[5] and we divide *icu* and *ccu* by state population data from the U.S. Census Bureau[6] to make them both per 100,000 population.

[3] Or, as documented in Dey and Lowenstein (2020), substantial effects on particular sectors of the labor market.

[4] The question of the impact of SAHOs on unemployment is further complicated by state-level differences in unemployment insurance. State implementation of unemployment insurance varies in myriad dimensions including occupational eligibility, waiting periods, calculation, duration and range of benefits, as well as deductions from benefits (U.S. Department of Labor 2020). While these differences likely impact levels of and perhaps changes in unemployment in the states, full consideration of these differences is beyond the scope of this paper.

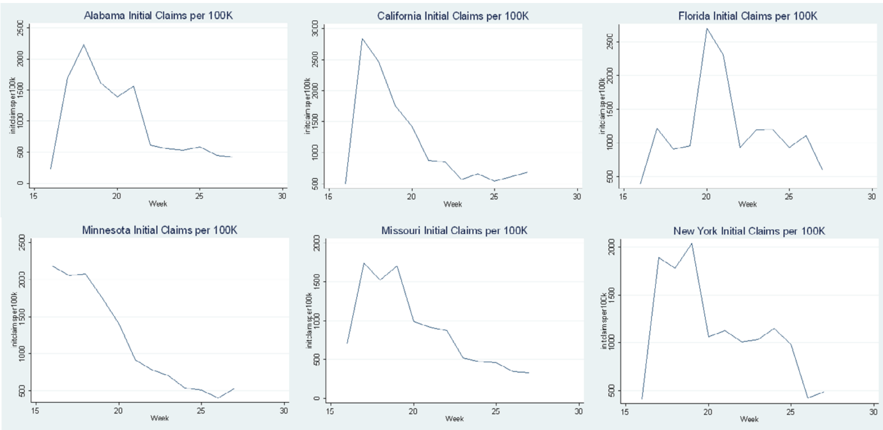
[5] https://oui.doleta.gov/unemploy/claims_arch.asp.

[6] https://www.census.gov/programs-surveys/geography/guidance/geo-areas/urban-rural/2010-urban-rural.html.



* All 50 states are available from the authors upon request.

Fig. 1 Insured Unemployment Rate (*urate*), for Selected States

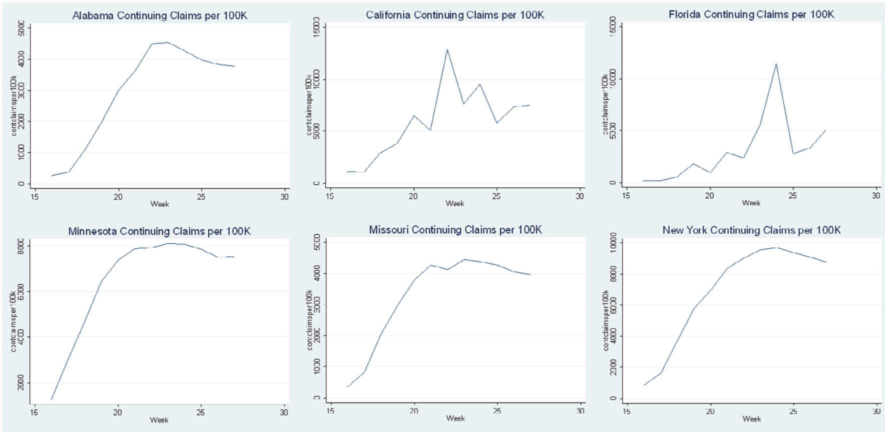


* All 50 states are available from the authors upon request.

Fig. 2 Initial Unemployment Claims (*icu*), per 100,000, for Selected States

We model unemployment in a state as a function of whether or not that state had a SAHO in place (*saho*), how broadly SAHOs were applied in the other 49 states (*pxsaho* – defined in detail below), and that state's weekly reported new COVID-19 cases (*cases*).[7] In particular, *saho* and *pxsaho* will show us the relative impact of a state's own SAHO, versus the prevalence of SAHOs in the rest of the country.

7 Unemployment was also modeled with COVID-19 mortality (*covid*) replacing *cases*. Most results were robust to this change and these results are available from the authors upon request.



* All 50 states are available from the authors upon request.

Fig. 3 Continuing Unemployment Claims (*ccu*), per 100,000, for Selected States

A SAHO (*saho*) is defined as a governor issued state-wide stay-at-home order. SAHOs that pertained only to particular cities are not utilized as data points in this analysis. As such, there are a few states in the dataset (as in real life) that never implemented a state-wide SAHO at all – see Table 1.[8]

The prevalence of SAHOs in the rest of the country outside a given state (*pxsaho*) is calculated uniquely for each state and is equal to the sum of the GDP of all other states with a SAHO in that week, divided by the total GDP of the 49 other states, giving us an economy-weighted measure of SAHO in the rest of the country. This variable captures the national SAHO level, in other words, in a manner that reflects levels of economic activity. The mean percentage of *pxsaho* ranged from just below 15% when California implemented the first SAHO in late March and peaked at just over 95% in mid-April. State-level GDP data come from Bureau of Economic Analysis Regional Economic Accounts website and data from the second quarter of 2020 are used.[9] The time path of both the percentage of states with SAHOs and this percentage weighted by state GDP is given in Figure 4; the two are closely related, justifying the use of *pxsaho* as a measure of national prevalence of SAHO implementation. *pxsaho* is at times slightly higher than the percentage of states with SAHOs because states with larger economies were more likely to implement SAHOs and to leave them in place longer.

[8] SAHOs were also not equivalently implemented or enforced across states. As such, the estimates on *saho* can be considered base rates of the impact of SAHOs on subsequent unemployment measures, particularly in states that had heterogeneous county level adoption first (Dave et al. 2020).

[9] https://apps.bea.gov/regional/downloadzip.cfm.

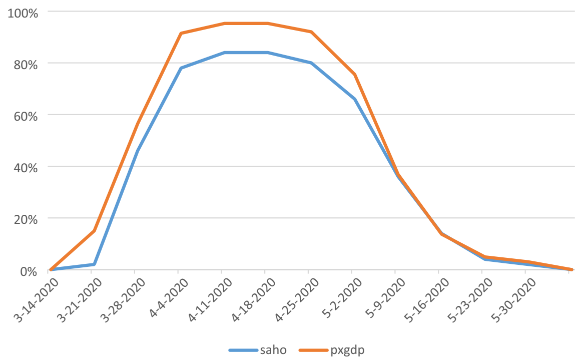


Fig. 4 Proportion of States with a SAHO and GDP Weighted SAHO, By Week

Table 2 Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Insured unemployment rate (*urate*)	1800	6.470	5.897	0.320	31.200
Initial unemployment claims per 100K (*icu*)	1800	471.881	596.789	18.531	4027.105
Continuing unemployment claims per 100K (*ccu*)	1800	3026.965	2770.788	168.834	15546.880
SAHO Week Dummy Variable (*saho*)	1800	0.138	0.345	0	1
Ex-State GDP SAHO (*pxsaho*)	1800	0.161	0.318	0	0.962
COVID Cases per 100k (*cases*)	1800	38.300	60.640	0	418.418

Data on a state's case experience with COVID-19 (*cases*) come from the Centers for Disease Control (CDC).[10] The CDC reports new cases reported daily. These were aggregated to weekly numbers.[11] We expect that, independent of a SAHO, higher rates of COVID-19 cases will have larger impacts on measures of unemployment as residents, hearing of increasing infection rates within their state, would presumably take some action to distance or isolate themselves, negatively impacting income and spending.[12]

Summary statistics of the data are provided in Table 2.

A potential complication in this work is that the implementation of SAHOs might be endogenous and that a state's unemployment or COVID experience may, in turn, be driving its decision to initiate or extend a SAHO. Two recent papers, however, by Amuedo-Dorantes et al (2020) and Kosnik and Bellas (2020), examined drivers

[10] https://data.cdc.gov/Case-Surveillance/United-States-COVID-19-Cases-and-Deaths-by-State-o/9mfq-cb36.

[11] Data on a state's mortality experience with COVID-19 (*covid*) come from the Centers from Disease Control (CDC). The CDC reports weekly excess deaths for each state attributed to all causes and to non-COVID-19 causes. Subtraction gives a measure of the weekly COVID-19 deaths in a state.

[12] There were certainly noteworthy examples of people intentionally congregating in the face of the pandemic and in defiance of public health recommendations, but if a significant portion of the population chose to shelter at home and distance themselves, the numerous, and heavily reported exceptions are likely to be less important economically than they were journalistically.

Table 3 *P* values from unit root tests for unemployment measures and first-differenced (fd) unemployment measures*

	icu	FD icu	ccu	FD ccu	Urate	FD urate
Levin–Lin–Chu	0.000	0.000	0.000	0.000	0.000	0.000
Harris–Tzavalis	0.000	0.000	**0.997**	0.000	**0.996**	0.000
Breitung	0.000	0.000	**0.947**	0.000	**0.943**	0.000
Im–Pesaran–Shin	0.006	0.000	**1.000**	0.000	**1.000**	0.000
Hadri	**0.000**	0.999	**0.000**	0.075	**0.000**	0.105

*Bold results indicate test results suggesting a unit root. All tests have as their null hypothesis a unit root except for the Hadri Lagrange multiplier test, whose null is stationarity.

**Results are presented for unit root tests that exclude a time-trend variable.

of SAHOs and other NPIs and found that both economic and epidemiologic factors were far outweighed by time-invariant state-level political factors (such as political party, Republican or Democrat) in explaining both the initiation and duration of statewide SAHOs and NPIs. We take these state political conditions to be predetermined and exogenous, thereby alleviating endogeneity concerns with respect to this work.

Models and Results

We use a standard longitudinal model to estimate the impact of each state's SAHO, the national weighted SAHO rate, and a state's COVID-19 new case rate on each of the three weekly measures of unemployment. Our econometric model is as follows:

$$y_{it} = \beta_0 + \beta_1 saho_{it} + \beta_2 pxsaho_{it} + \beta_3 cases_{it} + u_i + \varepsilon_{it} \tag{1}$$

where y_{it} is the unemployment measure in state i in period t, $saho_{it}$ is a dummy variable indicating that a statewide SAHO is in effect in state i in period t, $pxsaho_{it}$ is the percentage of GDP outside of state i that is subject to SAHOs in period t, $cases_{it}$ is the number of newly reported COVID-19 cases per 100,000 population in state i in period t, u_i is a state fixed effects term capturing unobserved, time-invariant state-level characteristics including such factors as differences in unemployment compensation rules, and ε_{it} is the usual error term for state i in period t.

As these are panel data describing states' unemployment experiences during the first wave of the pandemic, a reasonably discrete event, the question of the stationarity of the unemployment measures should be addressed. We conducted a battery of unit root tests on the three unemployment measures and their first differences.[13] The results of these tests are presented in Table 3. While the various tests yielded different results, evidence suggests that *icu* was stationary, while *ccu* and *urate* were not

[13] Tests conducted are as described for *xtunitroot*, panel-data unit-root tests, in StataCorp (2019), pp. 556-586.

stationary over the time period examined here. First differencing was used to render *ccu* and *urate* series stationary.

Specifically, the lagged version of equation (1) was subtracted from the contemporaneous version of equation (1) to yield the first differenced equation:

$$\begin{aligned} y_{it} - y_{i,t-1} = \beta_1 \left(saho_{it} - saho_{i,t-1} \right) + \beta_2 \left(pxsaho_{it} - pxsaho_{i,t-1} \right) \\ + \beta_3 \left(cases_{it} - cases_{i,t-1} \right) + \varepsilon_{it} - \varepsilon_{i,t-1} \end{aligned} \tag{2}$$

It should be noted that when the fixed effects model is first differenced, the fixed effects term is lost, with the resulting being a model that can be estimated using ordinary least squares.

The first model (1) was estimated for initial unemployment claims per 100,000 population (*icu*) using a random effects model with state-clustered standard errors.[14]

The second model (2) was estimated for continuing unemployment claims per 100,000 population (*ccu*) and for the insured unemployment rate (*urate*), using ordinary least squares with state-clustered standard errors and assuming a zero constant term.[15]

Models for all three dependent variables were estimated with *saho* alone, *pxgdp* alone, and with both *saho* and *pxgdp* together, in addition to *cases* as explanatory variables. Results are provided in Table 4.

Not surprisingly, the estimated coefficients on *saho* are positive and significant in all models for all three measures of unemployment. When a state implements a SAHO, *icu*, *ccu* and *urate* all rise.

More interesting, however, is that impacts from SAHOs outside the state, as represented by *pxgdp*, seem to dominate the impact of a state's own SAHO, as indicated by larger estimated coefficients on *pxgdp* when each is included individually, but especially when both *saho* and *pxgdp* are included together. The magnitude of the difference depends on the measure of unemployment and the model or models considered.

When initial claims are modeled as a function of *saho* and *cases*, the estimated coefficient on *saho* is 1090.029, whereas when initial claims are modeled as a function of *pxgdp* and *cases*, the estimated coefficient on standardized *pxgdp* is 1357.809. The literal interpretation is that the impact on a given state's initial unemployment claims of SAHO adoption across *the rest of the country* is about 1.246 times the impact of SAHO adoption within the state itself, with factors of 2.206 and 2.228 for continuing claims and the unemployment rate. The more intuitive

[14] A Hausman specification test failed to reject the null hypothesis that the random effects model was consistent, but both random effects and fixed effects models were estimated with both robust and state-clustered standard errors. The results were robust to changes in the specification. In addition, the model was estimated using COVID deaths rather than cases and results were robust to this change as well except that initial claims were not significantly impacted by deaths but were positively and significantly impacted by newly reported cases. Full results are available from the authors.

[15] Relaxation of these conditions did not substantially change the results. Results using fixed effects estimation, mortality rather than cases, and standardized values of the explanatory variables are available from the authors in an appendix.

Table 4: Estimated coefficients and p-values for initial claims per 100K, Continued claims per 100K and insured unemployment rate

Unstandardized values of SAHO and PXGDP

	Initial claims			FD continuing claims			FD unemployment rate		
saho	1090.029 *** (0.000)		159.066 * (0.083)	494.269*** (0.000)		256.584** (0.029)	1.040*** (0.000)		0.532** (0.036)
pxgdp		1357.809*** (0.000)	1221.063*** (0.000)		1090.593 (0.000)	875.848***(0.000)		2.317*** (0.000)	1.871*** (0.000)
Cases	0.888 (0.235)	1.036*** (0.000)	0.987*** (0.000)	3.665*** (0.001)	2.790*** (0.004)	2.744*** (0.004)	0.008*** (0.001)	0.006*** (0.004)	0.006*** (0.005)
Ratio of estimated coefficients of pxgdp and saho		1.246	7.676		2.206	3.413		2.228	3.517

Initial claims were modeled using a random effects model with state-clustered standard errors. Continuing claims and unemployment rate were modeled using ordinary least squares with no constant and state-clustered errors.

***Significant at the 1% level

**Significant at the 5% level

*Significant at the 10% level

explanation is that the state of SAHO in the rest of the country has a greater impact on a state's unemployment than does its own SAHO status.

When both *saho* and *pxgdp* are included as explanatory variables, the estimated differential impacts are even larger. The estimated coefficient on *pxgdp* ranges from 3.413 to 7.676 times as large as the estimated coefficient on *saho*. Again, the implication is that while a SAHO within a state impacts that state's unemployment measures, the stronger impact comes from SAHOs in other states nationwide. This is a new result, not previously documented in the literature.

Estimated coefficients on the COVID case rate (*cases*) are positive and usually statistically significant for both initial and continuing claims and the unemployment rate, suggesting that increases in COVID cases in a state also resulted in unemployment. While the estimated coefficients presented here suggest that impact of either *saho* or *pxgdp* dominated the impact of *cases*, results using standardized values of the explanatory variables suggest that for both continued claims and the overall unemployment rate, an increase of one standard deviation in the COVID case rates had a bigger impact than did a one standard deviation increase in *saho*, but not *pxgdp*.[16] For initial claims, *saho* and *pxgdp* have a larger impact than *cases*. With respect to the relative importance of SAHO versus COVID, our paper's results straddle those of Beland et al. (2020) and Gupta et al. (2020) as well as those of Forsythe et al. (2020), Rojas et al. (2020), and Kong and Prinz (2020).[17]

Overall, our results imply that both the pandemic itself and SAHOs, *especially at the national level,* increased multiple measures of unemployment. While there are subtleties in the relationship, the national experience of SAHOs seems to have been more important to every measure of a state's unemployment experience than whether or not that state implemented a SAHO itself.

Conclusion

The COVID-19 pandemic had a swift and devastating impact on the US economy in the spring of 2020. There has been some question, however, as to whether it was the pandemic itself, or subsequent state-level lockdowns, that most affected quickly rising unemployment measures. This paper examines the impact on various state-level unemployment rates of three associated drivers, to try and discern their disparate effects: individual states' SAHOs, the weighted national level of SAHOs, and states' rates of newly reported COVID cases.

Our results suggest that state-level SAHOs resulted in increased unemployment in a state, by any measure, but more important than any individual state's SAHO was the level of implementation of SAHOs nationwide; that appears to have had

[16] Results from standardized analysis are available upon request from the authors.

[17] These results should not be interpreted as taking a position on SAHOs, either at an individual state or at a national level. A proper benefit-cost analysis of SAHOs would require some measure of the costs of unemployment, but also of the benefits of implementation of SAHOs to reduced COVID infections and death rates.

an impact on a state's unemployment that dominates that of a state's own decision about SAHO, as well as newly reported infection rates.

Many statewide SAHOs were strongly opposed by state residents due in part, though not entirely, to projected unemployment impacts. Our analysis suggests that these objections, while not entirely unjustified, are somewhat misdirected as the actions taken in other states may well be more important than the actions taken within a state itself. Further, states that chose not to impose SAHOs in hopes of maintaining employment levels may have experienced increases in unemployment approaching what they would have incurred had they implemented SAHOs.

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