The influence of stay-at-home measures due to COVID-19 on unemployment in the USA

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Abstract

The quick spread of COVID-19 in the USA forced many states to establish social distancing measures. Those measures have had an impact on the economy, and many businesses had to lay-off people or postpone hiring processes. Until April 14th, almost 22 million Americans had filed for initial unemployment benefits in a month[1], which represents a historical record. In our analysis, we are focusing on investigating the effects of the stay-at-home orders on unemployment. The results of our analysis have many real-world implications, as we expect to provide a measure of the impact of stay-at-home orders on unemployment insurance claims and unemployment rates that could be used in the future by decision-makers to plan and implement mitigation/recovery measures.

1. Motivation

We are currently experiencing one of the deadliest pandemics in human history. As of now, the effects in the economy due to travel restrictions, stay-at-home/shelter-in-place orders, closure of small businesses, and so on are starting to be evident and concerning in many countries.

In the USA at least 42[2] out of 50 states have asked their residents to avoid leaving home unless they work for essential businesses or to perform essential activities such as go to the grocery store, attend medical appointments or take care of an affected family member. As a consequence, businesses are facing a large decrease in sales and revenues, which causes workers to be laid off and some companies have frozen hiring processes. According to a study[3] published by the Federal Reserve Bank of St. Louis on March 24, the unemployment rate could reach 32% in the second quarter of the year.

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1 https://www.nbcnews.com/business/economy/unemployment-claims-state-see-how-covid-19-has-destroyed-job-n1183686

2 As of April 20, 2020.

3 www.stlouisfed.org/on-the-economy/2020/march/back-envelope-estimates-next-quarters-unemployment-rate

As a result of this analysis, we will be able to measure the impact of the actions taken to stop the spread of the COVID-19 virus on unemployment. For the analysis of unemployment claims, our results are representative of only beneficiaries of federal unemployment insurance who are citizens or eligible to work non-citizens that meet the criteria to be insured.

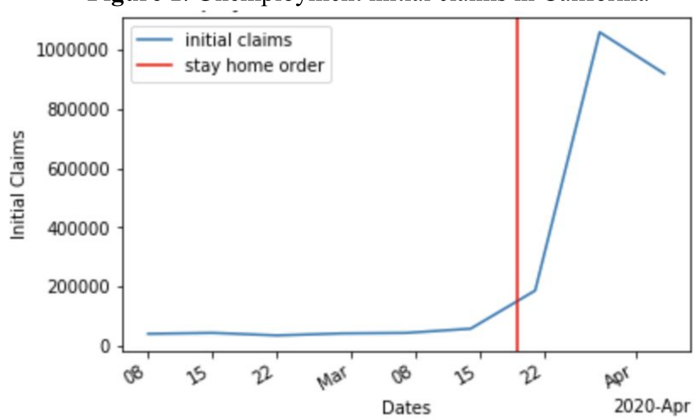
2. Data

2.1. Unemployment data

We collect two types of unemployment information:

A. Unemployment insurance weekly claims[4] in each state from the United States Department of Labor. These records represent only beneficiaries of federal unemployment insurance who are citizens or eligible to work non-citizens that meet their state's criteria to be insured. As an example, Figure 1 represents the initial unemployment claims in the state of California this year. The red vertical line represents the date when the stay at home order was enforced in that state.

Figure 1. Unemployment initial claims in California



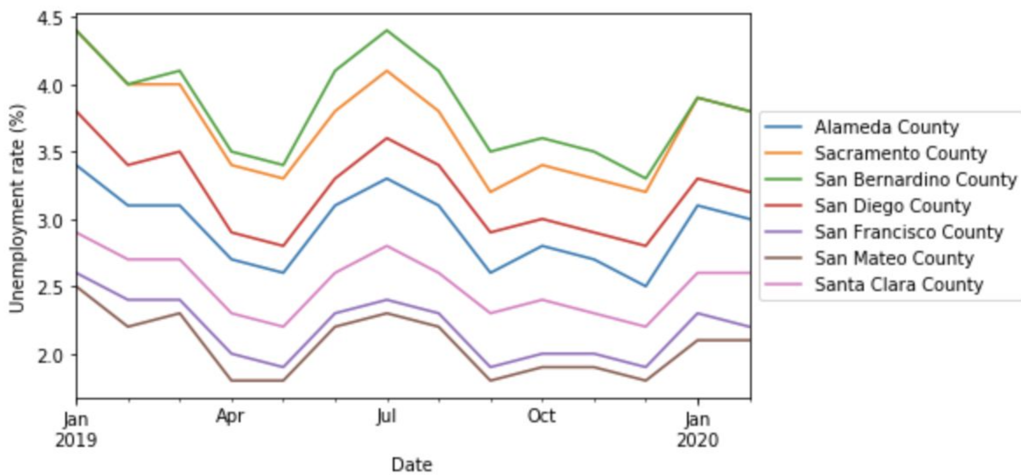
	Initial unemployment
Count	223.0
Mean	3680.8
Std.	8760.7
Min.	1575.0
25%	2253.0
50%	2550.0
75%	3132.5
Max.	106739.0

B. Unemployment rates[5] for states and counties reported on a monthly basis from the United States Bureau of Labor Statistics. Figure 2 represents the trend in unemployment rates for some counties in California from 2019 as of the last data available (February 2020).

The unemployment insurance claims will serve as a proxy for the states' unemployment rate and will provide us with more recent and granular information about the disruption in the labor market due to the COVID-19 pandemic.

[4] United States Department of Labor: https://oui.doleta.gov/unemploy/claims.asp
[5] United States Bureau of Labor Statistics: https://www.bls.gov/web/laus/laumstrk.htm

Figure 2. Unemployment rate (%) in some counties in California



2.2. Individual Mobility data

The data was provided by the SafeGraph COVID-19 Data Consortium and includes records of tracking mobility of devices as a proxy of the owners. The unit of information is the daily observations by census block groups across the US from January 1st to April 20th. It contains 13 variables that describe anonymized data of individuals such as distance traveled from home or the number of minutes individuals dwell at home. The strategy to identify the home of users is to track the common nighttime location of each mobile device over a 6 week period.

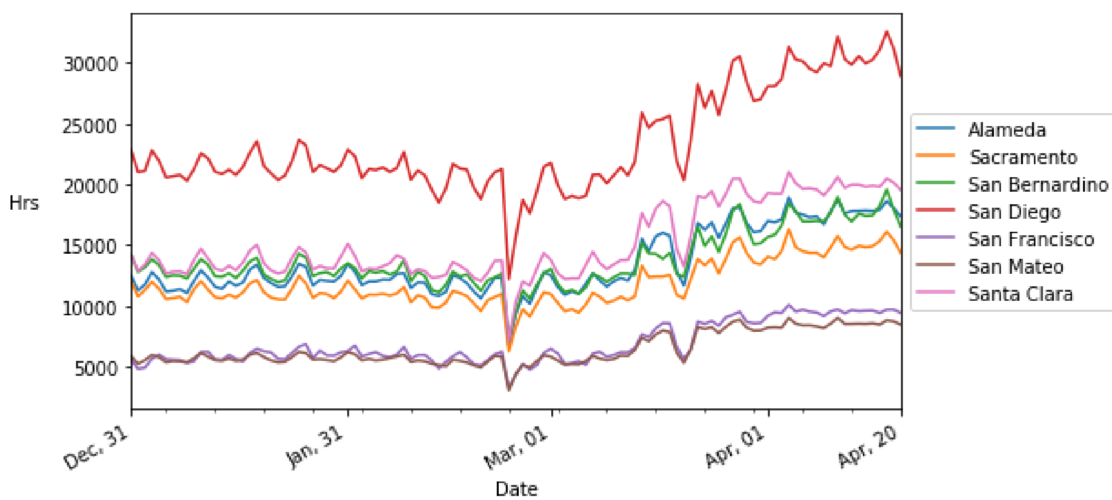
111 files were downloaded in gzip format (1.9GB with subfolders for month and date). In order to facilitate the manipulation, we first explored structure, format, and content. We used an iterative process to read and aggregate each file in a data frame. For our analysis, the relevant columns are:

- Origin census block group - The unique 12-digit FIPS code for the Census Block Group. If the cell did not contain 12-digit format, we added a zero-digits in front
- Date_range_start and end - Start and end time of daily measures
- Median_dwell_home_time - Median dwell time at home geohash-7 **in minutes** for all devices in the device_count during the time period. For each device, Safegraph summed the stops at home and then found the median of the sums.

In order to identify the corresponding census block group (CBG) with counties and states, we extracted the first 5 digits from the CBG that identify the state (first 2 digits) and county (following 3 digits). The FIPS code for each state and county was downloaded from the Natural

Resources Conservation Service[6]. The dataset was saved as CSV and merged on the FIPS column with the Safegraph mobility data set in order to have as units of observation for our analysis: Date, county, state were grouped and median home dwell time was summed across all CBG corresponding to each county and transformed into hours. In figure 3, we present visualizations of the trend in mobility for some counties in California. We appreciate an upper trend during the first week of March that accentuates at the beginning of April and reaches a new level in all counties.

Figure 3. Median home dwell time (hrs.) in some counties in California



2.3. Stay-at-home order

The stay-at-home orders issued by the states are summarized in The New York Times article[7] along with the specific date the order was enforced. The states with partial stay-at-home orders were not taken into account for this analysis. The unit of observation indicates the state and date the stay-home order was enforced.

The stay home order dataset was merged on the state column for the weekly unemployment insurance claims across all US dataset. California's unemployment rates by month, between January and March 2020, was merged with the Safegraph mobility data set included both county and state levels by day, so it was grouped according to the unit of information required: date, county, metrics in California, or date, state, metrics for all US. Both data sets were indexed on date.

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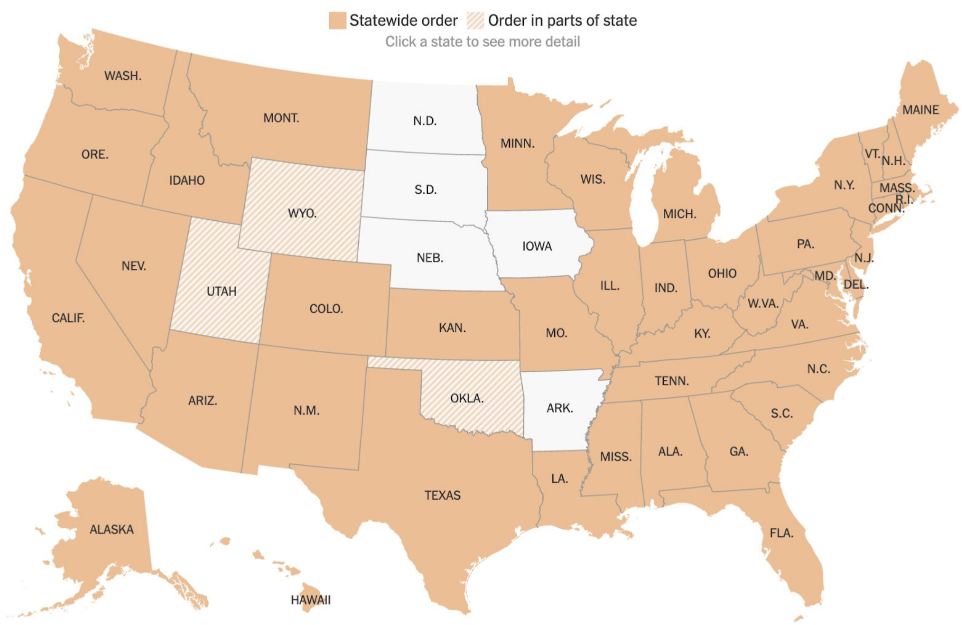
[6] Natural Resources Conservation Service: https://www.nrcs.usda.gov/wps/portal/nrcs/detail/national/home/?cid=nrcs143_013697

[7] Stay-at-home orders: https://www.nytimes.com/interactive/2020/us/coronavirus-stay-at-home-order.html

Figure 3. Statewide stay-at-home orders



Source. The New York Times

3. Methods and results

3.1 County Level

The county-level data available as of April 28, 2020, is the following:

- Monthly unemployment rates for all USA counties (Jan 2019 - Feb 2020).
- Monthly unemployment rates for California state' counties (Jan 2019 - March 2020).
- Daily mobility data for all USA counties (Jan 2020 - April 2020).

It is worth noting that even though the first Coronavirus case confirmed in the USA occurred by the end of January 2020, the stay-at-home measures took place later in March 2020. *Thus, we will discard the analysis of unemployment rates for all USA counties since we do not have information beyond February 2020*. However, the California Department of Labor published its unemployment rate records as of March 2020. We will analyze the effect of dwell time at home (mobility SafeGraph data) on unemployment rates this year in California, one of the hardest-hit states in the USA.

3.1.1 Fixed effects - California counties & mobility data

We will perform a fixed-effect model to control for variations between counties in California and time dependencies. In particular:

$$Unemployment\ rate_{CA} = \alpha + \beta_1\ Dwell\ time\ at\ home_{median} + \beta_2\ County\ + \beta_3\ Month_{2020} + \epsilon$$

And we are interested in the sign and magnitude of the β_1 coefficient. The results in Appendix, Table 1 suggest that there is no statistically significant effect of individual mobility measures on the unemployment rate for counties in California. As we observed in Figure 1, the upper trend in March is preceded by a sharp decline, so when we use the mean of the time dwell at home, the resulting average equals the average amount of time registered during January. The effect of the increase of the time dwell at home could be significant if we were able to include in the model the unemployment rate of April. It is also possible that we are not observing any effect because of the lack of granularity in the unemployment rate data (we observe monthly data points only).

3.2 State Level

The state-level data available as of April 28, 2020, is the following:

- Weekly unemployment insurance claims for all USA states (Jan 2019 - Apr 2020), grouped as claims per 10,000 people.
- Date of governmental statewide stay-at-home orders for all USA states.
- Daily mobility data for all USA counties (Jan 2020 - April 2020).

Given the granularity and availability of recent data, we will perform (1) a fixed-effects model to analyze the impact of dwell time at home (mobility SafeGraph data) on unemployment insurance claims and (2) a difference-in-difference with state and week fixed effects approach to identify if the stay-at-home order has an impact on unemployment insurance claims.

3.2.1 Fixed effects - mobility data

In this analysis, we aggregated the mobility data by state and by week to merge this information with the weekly unemployment insurance claims. We added fixed effects for state and week to control for time dependencies and peculiarities of each state. The specification of the regression is the following:

$$Unemployment\ insurance\ claims = \alpha + \beta_1\ Dwell\ time\ at\ home_{median} + \beta_2\ State\ + \beta_3\ Week_{2020} + \epsilon$$

Again, we are interested in the β_1 coefficient to identify if the time spent at home has an impact on unemployment insurance claims. The results that are shown in Appendix, Table 2 suggest that there is a positive and statistically significant effect of time at home on unemployment insurance claims. In particular, an additional minute in the median time spent at home increases the number of unemployment claims by 1.07.

3.2.2 Fixed effects - stay-at-home order indicator

In this approach, instead of using individual mobility as a measure of staying-at-home, we employ an indicator variable that takes the value of 1 if there is an official stay-at-home order imposed statewide. We added fixed effects on the state and on a week variable that accounts for the four weeks after and the four weeks before the stay-at-home order was enforced. This is the equation specification:

$$Unemp.\ insurance\ claims = \alpha + \beta_1\ Stay\ at\ home\ order_{indicator} + \beta_2\ State\ + \beta_3\ Week_{2020}\ + \epsilon$$

In this regression, we are interested in the significance level and the magnitude of β_1. The results in Appendix, Table 3 suggest that there is a significant effect of stay-home-order order on the unemployment rate. With the stay-at-home order implemented, the number of unemployment filings per 10,000 people is 87 more than the states without the order in place.

3.2.3 Pre-post/treated-control with fixed effects - stay-at-home order indicator

We further analyzed the impact of stay-at-home order on unemployment at the state-level by performing a diff-in-diff analysis. We are aware that there might be a spillover effect between states with official stay-at-home orders and states without, in which case we would be violating the SUTVA assumption. Thus, we will be cautious inferring causality from this exercise but we consider it interesting to see if there is an effect of nationwide efforts to stay-at-home on unemployment.

To perform a diff-in-diff analysis we have to test that both control and treated states have parallel trends in the pre-treatment period (Jan 2020 - mid-March 2020). A more flexible approach is to add fixed-effects per (1) state to control for potential differences between states that do not vary in time and fixed-effects per (2) week to account for the progression of the economic crisis in time.

We will perform the second pre-post / treated-control approach with the following specification:

$$\begin{gathered}Unemp.\ insurance\ claims = \alpha + \beta_1\ StayAtHome\ order_{indicator} + \beta_2\ Post\ order_{indicator} \\ + \beta_3\ StayAtHome\ order * Post\ order\ + \beta_4\ Week_{2020} +\ \beta_5\ State +\ \epsilon\end{gathered}$$

Where the stay-at-home order (treatment) and the post-order (post-treatment) variables are indicators taking the values 0 or 1. The stay-at-home order takes the value of 1 in states that implement this policy and 0 in those states that never implemented the policy. The post-order (post-treatment) indicator takes the value of 0 for the four weeks prior to the order and takes the value of 1 for the four weeks after the order was imposed. For the states that did not implement a stay at home order, the post-treatment period will be the four weeks before March 21 and the pre-treatment period will be after March 21.

The difference-in-difference estimator is the one from the interaction term of the stay-at-home order and post-treatment indicators, β_3. The results in Appendix, Table 4 suggest that the stay-at-home order indicator and post-order indicator alone are not significant, whereas the interaction between order indicator and treatment indicator is positive and statistically significant.

For the post-treatment period, states with stay-at-home orders are expected to have 86,590 more unemployment claims compared with states in the pre-period and without stay-at-home orders. For the pre-treatment period, states with stay-at-home orders are expected to have 31,860 more unemployment filings than states without the order. For the post-treatment period, states with stay-at-home orders are expected to have 118,450 (86,590 + 31,860) more unemployment filings than states without the order.

4. Conclusion

4.1 County Level

As we observed from the county-level analysis in California, there is no statistically significant effect of dwell time at home in the unemployment rate, at least from the period between Jan 2020 - March 2020. Given that the unemployment rate indeed increased during that period, this result suggests that despite government efforts to make people stay at home, individuals are spending time outdoors either way.

Another reason why we did not observe a significant effect could be due to the seasonality on the unemployment rates. January tends to be one of the months with the highest unemployment rates. Thus, the increase in unemployment from January to March does not seem as big as it actually is. In future work, it would be ideal to adjust for seasonality.

4.2 State Level

For the state-level analysis, the unemployment measure is weekly unemployment insurance claims. The results suggest that both (1) dwell time at home and (2) stay-at-home orders have a positive and statistically significant effect on unemployment claims when controlling for state and week. The different results between the state and the county level analyses could rely on the availability of recent data.

Lastly, from the diff-in-diff with fixed effects approach, we can conclude that the governmental efforts to flatten the curve of infections by means of issuing stay-at-home orders have had a positive and statistically significant effect on unemployment insurance claims. It is worth noting that our results are conservative since unemployment insurance can only be claimed by a subgroup of the total population.

In sum, even if the measures issued to close schools and workplaces, cancel social events, and ask people to stay-at-home have been effective in decreasing the velocity and volume of infections, those measures have had a huge effect on the economy. Unemployment is only one of the many indicators that have been negatively impacted.

Sources

- https://www.nytimes.com/interactive/2020/us/coronavirus-stay-at-home-order.html
- https://www.stlouisfed.org/on-the-economy/2020/march/back-envelope-estimates-next-quarters-unemployment-rate
- https://oui.doleta.gov/unemploy/claims.asp
- https://fred.stlouisfed.org/series/UNRATE#0
- https://www.nrcs.usda.gov/wps/portal/nrcs/detail/national/home/?cid=nrcs143_013697
- https://www.bls.gov/web/laus/laumstrk.htm

Appendix

Table 1. OLS California counties regression results - Fixed effects (dwell time at home)

Dep. Variable:	unemp_rate	**R-squared:**	0.982
Model:	OLS	**Adj. R-squared:**	0.972
Method:	Least Squares	**F-statistic:**	104.4
Date:	Tue, 28 Apr 2020	**Prob (F-statistic):**	1.44e-77
Time:	15:08:54	**Log-Likelihood:**	-121.92
No. Observations:	174	**AIC:**	363.8
Df Residuals:	114	**BIC:**	553.4
Df Model:	59		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	1.2055	0.822	1.467	0.145	-0.422	2.833
county[T.Alpine]	2.9064	0.912	3.189	0.002	1.101	4.712
county[T.Amador]	2.1574	0.896	2.409	0.018	0.383	3.932
...						
county[T.Yolo]	2.4646	0.837	2.945	0.004	0.806	4.123
county[T.Yuba]	4.7788	0.884	5.407	0.000	3.028	6.530
median_home_dwell_time	8.476e-07	1.02e-06	0.834	0.406	-1.17e-06	2.86e-06
month	0.7269	0.058	12.475	0.000	0.611	0.842

Omnibus:	5.960	**Durbin-Watson:**	2.549
Prob(Omnibus):	0.051	**Jarque-Bera (JB):**	5.739
Skew:	0.441	**Prob(JB):**	0.0567
Kurtosis:	3.121	**Cond. No.**	9.98e+07

Table 2. OLS state regression results - Fixed effects (dwell time at home)

OLS Regression Results

Dep. Variable:	initial_claims	**R-squared:**	0.518
Model:	OLS	**Adj. R-squared:**	0.471
Method:	Least Squares	**F-statistic:**	10.86
Date:	Tue, 28 Apr 2020	**Prob (F-statistic):**	1.83e-66
Time:	16:34:42	**Log-Likelihood:**	-8665.4
No. Observations:	700	**AIC:**	1.746e+04
Df Residuals:	636	**BIC:**	1.775e+04
Df Model:	63		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	-2.469e+04	1.81e+04	-1.361	0.174	-6.03e+04	1.09e+04
state[T.AL]	-2850.1542	2.35e+04	-0.121	0.904	-4.9e+04	4.33e+04
...						
week_ended[T.Timestamp('2020-04-04 00:00:00')]	1.097e+05	1.22e+04	8.988	0.000	8.57e+04	1.34e+05
week_ended[T.Timestamp('2020-04-11 00:00:00')]	8.423e+04	1.23e+04	6.875	0.000	6.02e+04	1.08e+05
median_home_dwell_time	1.0708	0.305	3.514	0.000	0.472	1.669

Omnibus:	771.612	**Durbin-Watson:**	0.689
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	90718.189
Skew:	4.972	**Prob(JB):**	0.00
Kurtosis:	57.877	**Cond. No.**	3.42e+06

Table 3. OLS state regression results - Fixed effects (stay-at-home order indicator)

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	107.9227	19.226	5.613	0.000	70.068	145.778
C(order)[T.1]	87.0981	20.270	4.297	0.000	47.189	127.008
C(week)[T.-3]	16.1043	24.613	0.654	0.513	-32.356	64.565
C(week)[T.-2]	20.6262	24.036	0.858	0.392	-26.698	67.950
C(week)[T.-1]	19.4559	23.993	0.811	0.418	-27.784	66.695
C(week)[T.0]	-40.6414	23.993	-1.694	0.091	-87.881	6.598
C(week)[T.1]	-105.3178	23.993	-4.390	0.000	-152.557	-58.078
C(week)[T.2]	-147.8508	23.993	-6.162	0.000	-195.090	-100.611
C(week)[T.3]	-150.0040	23.993	-6.252	0.000	-197.244	-102.764
C(week)[T.4]	-176.1321	32.553	-5.411	0.000	-240.226	-112.038
C(State)[T.Alaska]	-12.8704	29.223	-0.440	0.660	-70.409	44.668
...						
C(State)[T.Texas]	-68.2658	30.565	-2.233	0.026	-128.445	-8.086
C(State)[T.Vermont]	-33.8299	29.507	-1.147	0.253	-91.926	24.266
C(State)[T.Virginia]	-47.3579	30.565	-1.549	0.122	-107.537	12.821
C(State)[T.Washington]	-19.6207	29.507	-0.665	0.507	-77.717	38.475
C(State)[T.West Virginia]	-99.0693	29.507	-3.358	0.001	-157.165	-40.973
C(State)[T.Wisconsin]	-53.5447	29.507	-1.815	0.071	-111.641	4.551

Omnibus:	33.373	**Durbin-Watson:**	1.509
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	54.975
Skew:	0.638	**Prob(JB):**	1.15e-12
Kurtosis:	4.575	**Cond. No.**	1.31e+16

Table 4. OLS state regression results - Diff-in-diff with fixed effects

Dep. Variable:	initial_claims	**R-squared:**	0.570
Model:	OLS	**Adj. R-squared:**	0.493
Method:	Least Squares	**F-statistic:**	7.345
Date:	Tue, 28 Apr 2020	**Prob (F-statistic):**	2.99e-28
Time:	21:14:06	**Log-Likelihood:**	-4058.8
No. Observations:	321	**AIC:**	8218.
Df Residuals:	271	**BIC:**	8406.
Df Model:	49		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	2.922e+04	1.53e+04	1.909	0.057	-910.107	5.94e+04
C(State)[T.Alaska]	-5.217e+04	4.54e+04	-1.148	0.252	-1.42e+05	3.73e+04
...						
C(State)[T.Washington]	1.583e+04	4.57e+04	0.346	0.729	-7.42e+04	1.06e+05
C(State)[T.West Virginia]	-7.054e+04	4.57e+04	-1.543	0.124	-1.61e+05	1.95e+04
C(State)[T.Wisconsin]	-2.737e+04	4.57e+04	-0.599	0.550	-1.17e+05	6.26e+04
order	3.186e+04	3.2e+04	0.997	0.320	-3.11e+04	9.48e+04
post_period	-4.768e+04	3.14e+04	-1.517	0.130	-1.1e+05	1.42e+04
order:post_period	8.659e+04	2.81e+04	3.080	0.002	3.12e+04	1.42e+05
week	-1.83e+04	4444.417	-4.117	0.000	-2.7e+04	-9549.311

Omnibus:	214.300	**Durbin-Watson:**	1.028
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	6742.117
Skew:	2.219	**Prob(JB):**	0.00
Kurtosis:	25.009	**Cond. No.**	2.25e+15