Labor Market Destruction and Unemployment Insurance Expansion due to COVID-19

Hannah Doochin and Klara Sabirianova Peter

Our research seeks to expand upon the existing, yet limited investigation of the relationship between COVID-19 and labor market destruction. Specifically, our intent is to uncover a correlation between the expansion of unemployment insurance benefits as a result of COVID and state unemployment rates. Our analysis leads us to conclude that the policies expanding benefits to those in quarantine and policies extending the duration of benefits have a statistically significant effect on unemployment rates, ceteris paribus. Stay-at-home mandate timing also has a significant effect on unemployment.

I. Introduction

The United States economy has seen a myriad of changes in the last nine months due to the implications of the global pandemic, COVID-19. With the closing down of nonessential businesses, stay-at-home mandates, and focus on safety and limiting spread, the U.S. and the Trump administration have taken various economic hits—especially in the labor market. The U.S. insured unemployment rate reached an all-time high of 14.7% in April with some states reaching an individual rate upwards of 25% ("United States Unemployment," 2020). 47 out of the 50 reached an all-time unemployment high in either April or May of this year ("Current Unemployment Rates," 2020). As the labor market has become more volatile since February of this year, so have the unemployment rates for each state. This paper seeks to understand what specific factors of COVID-19 and its consequences are most salient in assessing labor market destruction. These factors include the spread of the virus, each state's reaction and implementation of policy, and existing state demographics. The paper specifically seeks to understand how each state's unemployment rate has changed as states have implemented various unemployment insurance expansion policies as a result of COVID. The study uses available COVID-19 case and policy data, as well as unemployment claims provided by the United States Department of Labor, to analyze these factors.

II. Background on COVID and Unemployment

COVID-19 is a contractible disease caused by an unfamiliar strain of coronavirus that can result in symptoms such as fever, cough, and shortness of breath. The virus was declared a Public Health Emergency of International Concern (PHEIC) on January 30, 2020. The first diagnosed case in the US was on January 20, 2020 ("United States COVID-19 Cases," 2020). COVID-19 is transmitted when one person comes in contact with the respiratory droplets of another infected person, or from touching surfaces that have been contaminated with infection. According to the Center for Disease Control and Prevention (2020), there have been 6,825,697 cases in the U.S. and 199,462 deaths (as of September 22nd 2020). Some of the states that have seen consistently high rates of growth in COVID cases are Delaware, Maryland, Minnesota, Nebraska, New Mexico, North Dakota, Ohio, Rhode Island, and Virginia. New York and California have had large numbers of cases and deaths relative to other states. The number of total U.S. cases continues to rise. This could be due to increased rates of testing or a lack of appropriate state policy and enforcement of COVID rules.

Both federal and state level leaders have taken retroactive action to try to reduce the spread of COVID since early March. Common ways of addressing this spread have been: mandated stay-at-home orders, closing of nonessential businesses, and implementation of mask requirements. Stay-at-home orders, although they vary slightly by state, typically advise that people stay in their homes unless it's extremely necessary to go out in public. Closing of nonessential businesses and other organizations have included restaurants excluding take-out, schools and daycares, as well as any businesses deemed nonessential for survival. There is a high level of variance for dates that states started to close these types of businesses. Mask requirements require face-coverings in any public spaces, and mask mandates seemed to have come into effect later in 2020 than the first two responses.

While officials have taken steps to avoid the spread of COVID, closing of businesses and stay-at-home orders have disincentivized economic growth and led to stark spikes in unemployment rates. To help counteract the negative externalities that these actions have had economically, some states have implemented changes to their unemployment insurance policies. While these efforts might have somewhat reduced the economic decline, the U.S. is still seeing record high rates of unemployment and unemployment claims for benefits this year. According to the U.S. Bureau of Labor Statistics, the average unemployment rate for 2017, 2018, and 2019 were 1.3, 1.15, and 1.09 percent respectively, while the current average for 2020 is 8.4 percent (as of September 22nd 2020).

III. Existing Research

Because the spread of COVID-19 has happened so suddenly, and we know relatively little about the virus itself, there exists minimal literature on the relationship between COVID and unemployment. The U.S. has never experienced a national shutdown of this magnitude due to a global pandemic such as this one aside from the Spanish Flu in 1918. Thus, research explaining unemployment effects of this virus is non-expansive. This research hopes to expand on some of the established efforts in this field that are mentioned below.

Richard Cebula (2019) published a study in the Academy of Economics and Finance that looks at labor market freedom and its effect on the unemployment rate in the U.S. Cebula defines economic freedom in three ways: state minimum wage, proportion of state-level employees, and union characteristics/right-to-work legislation in that respective state. Cebula's research is helpful because it uses panel data over an eight year period that encompassed the Great Recession. By looking at state characteristics regarding economic freedom—a key element of current state policy in response to COVID—during an impactful time of low production and high unemployment, Cebula helps form answers to questions being asked during this pandemic. Cebula's research concludes that greater economic freedom results in lower unemployment rates (Cebula, 2019). This research does not focus specifically on economic restrictions pertaining to COVID-19, thus it is limited in its understanding of current unemployment effects.

Elizabeth Ananat and Anna Gassman-Pines (2020) published COVID research regarding the proportion of families actively seeking to acquire unemployment benefits during COVID. Their study illuminates the gap that existed at the start of COVID spread between families who lost their job and those that applied for Unemployment Insurance—not to mention the extended gap between those who finally received it. They found that only forty-five percent of people who had been laid off, had applied for unemployment insurance, and only four percent of those who had been laid off actually received unemployment insurance (Ananat & Gassman-Pines, 2020). For this reason, state unemployment claims might be skewed. States have progressively taken action to increase the accessibility and duration of their unemployment insurance since March of this year (Ananat & Gassman-Pines, 2020). This paper will try to understand if these efforts have helped lessen the gap between the newly unemployed and those applying for unemployment benefits—or the insured unemployment rate.

Béland et al. (2020) conducted research on the effect of COVID stay-at-home orders on unemployment and wages in the U.S.. Béland et al. (2020) take an intersectional approach on the way wages, labor force participation, and the unemployment rate have changed as a direct effect of stay-at-home mandates. They find that unemployment rates are significantly higher for states that implemented stay-at-home orders. This study was published in May of 2020 before the current effects of COVID policy had been introduced, therefore it does not account for states that may have implemented stay-at-home later than May 23rd, or the patterns of terminating stay-at-home orders and those effects on unemployment. It also does not look at the effects of unemployment insurance expansion in relation to stay-at-home orders.

A. Contributions

Our research seeks to expand upon the existing, yet limited investigation of the relationship between COVID-19 and unemployment. Specifically, our intent is to uncover a correlation between the expansion of unemployment insurance benefits as a result of COVID and state unemployment rates. As Béland et al. (2020) has already done, we want to examine how stay-at-home policies play a role in this. We do this by looking at both the correlation between early and late mandate implementation and termination, as well as the effect of stay-at-home mandates on unemployment during the time they were in effect. In addition we want to look at how other unemployment insurance expansion policies coinciding with the timing of stay-at-home mandates influence unemployment claims—building on the work done by Ananat and

Gassman-Pines (2020). Our research uses more current data than any of the aforementioned studies, hopefully capturing greater effects of the spread of COVID, the volatility of unemployment rates, and states' policy reactions.

B. Key Findings

Our research explores the effects of four unique policies that various states have implemented this year in response to COVID-19. These policies include: expansion of unemployment insurance (UI) to those in quarantine or taking care of someone in quarantine, expansion of UI to those who have lost childcare or been affected by school closures, expansion of UI to high-risk individuals in preventative quarantine, and extension of the amount of time an individual can receive UI benefits. Our analysis leads us to conclude that the policies expanding benefits to those in quarantine and policies extending the duration of benefits have a statistically significant effect on unemployment rates, ceteris paribus. Implementation of the quarantine extension had a negative correlation with unemployment, and extending the duration of UI had a positive correlation with unemployment.

We also explore effects of stay-at-home mandates, and the timing of these mandates. Our research finds that when controlling for COVID spread, states that implemented stay-at-home had slightly higher rates of unemployment compared to states that did not implement. Early implementation and late termination are correlated to higher rates of unemployment as well. While stay-at-home was in place, states that implemented the mandate had a large percentage point higher rate of unemployment than before the mandate was in place. After the policy was terminated, states that had implemented stay-at-home had an even larger percentage point higher rate than before the states had put this policy into effect.

This paper will begin with a description of the data sources used—as well as how these sources were manipulated to fit our research question. This data section will also include a descriptive analysis of some of the key elements and findings from the initial data sets including COVID spread, unemployment rates, policy implementation, and economic growth. There will then be a section describing the baseline empirical model that we have used, as well as our extensions of that model. This model controls for industrial composition, state fixed effects, and economic development. Lastly, we have provided a section explaining the results of our research and concluding the paper.

IV. Data Description

We are essentially working from four merged data sets: US Unemployment claims (updated weekly), US state policies (including time of implementation and time of termination, as well as state level characteristics pertaining to COVID), US COVID cases and deaths (updated daily), and state real GDP and per capita personal income (updated quarterly).

a. US Unemployment Claims:

This data is provided by the United States Department of Labor. We use data from the first week of January 2017 up until August 19th of 2020. The date reporting of the previous week's claims provides us with emerging unemployment claims and the current unemployment rate for a given state on a given week.

By looking at unemployment data beyond just the year 2020 we can compare rates of unemployment for each state on a weekly basis for the years leading up to the start of COVID spread. In doing so, we are able to compare any significant changes in unemployment rates in

2020 that may be correlated to COVID. To use this data, we dropped state categories Puerto Rico and the Virgin Islands, as those states are not typically included in US analysis, and there isn't COVID case or policy data available to merge. We then generated yearly, monthly, and weekly variables based on the DMY dates provided by the Department of Labor.

Figure 1- State Unemployment Rates for a Given Week in 2020

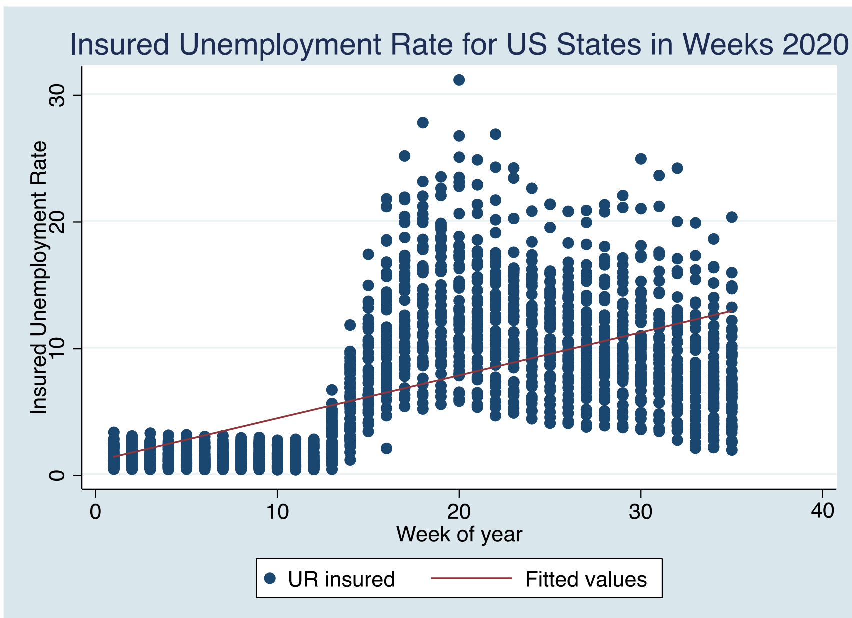


Table 1- Unemployment Summary Statistics 2017-2020

		Mean	*Standard Deviation*	*Minimum*	*Maximum*
2020	Initial Claims	31701.21	66305.65	159	1058325
	Unemployment Rate	7.23	5.79	.37	31.2
2019	Initial Claims	4234.35	6475.10	81	56886

	Unemployment Rate	1.10	.57	.17	3.47
2018	Initial Claims	4282.39	6527.41	120	58962
	Unemployment Rate	1.15	.61	.18	4.3
2017	Initial Claims	4710.07	7196.08	137	63788
	Unemployment Rate	1.31	.65	.22	4.92

As evidenced in Figure 1 and Table 1, states' unemployment rates in 2020 ranged from .5% to 31%. This is a much greater variation than 2019, which ranged from .5% to three and 3.5% unemployment. While peak state unemployment reached 31% in week nineteen of this year, it had a maximum average of roughly 10.5% in the previous three years (2017, 2018, and 2019). Also evidenced in Figure 1 is the sudden spike in unemployment rates around week 12 when the U.S. started to see its first influx of COVID cases. We see these same trends in Figure 2 when we look at the natural log of unemployment claims for a given state in a given week.

Figure 2- US Log Unemployment Claims in Weeks 2020

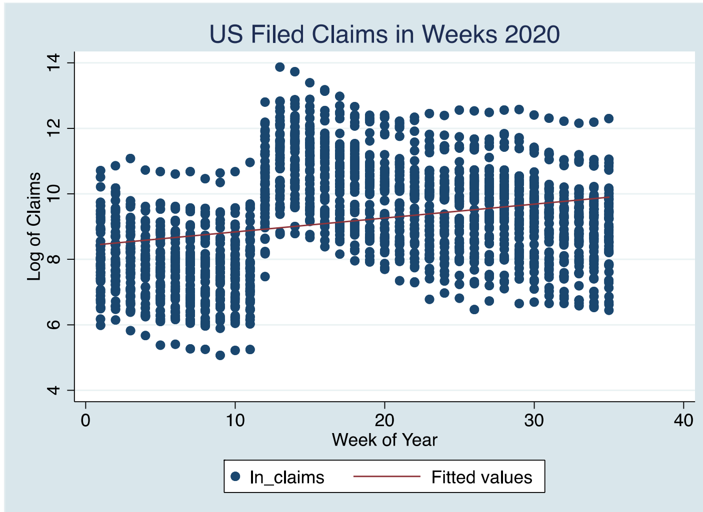


Figure 3- UR in Weeks 2020 for States with Consistently Low and High Unemployment

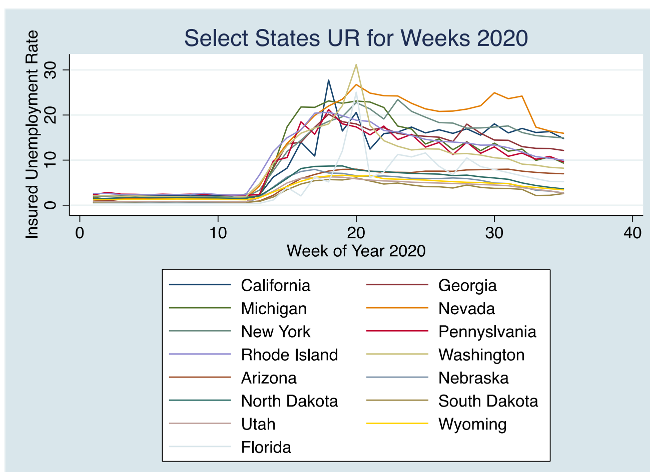


Figure 3 shows unemployment rates for each week in 2020 for states with consistently high and low unemployment. Top-unemployment rate states are California, Georgia, Michigan, Nevada, New York, Pennsylvania, Rhode Island, and Washington. At the time of this paper, states continuing to see higher than average unemployment rates are California, Connecticut, Hawaii, Louisiana, Nevada, and New York (as of September 22nd, 2020). Conversely, states with consistently low unemployment rates are Arizona, Nebraska, North Dakota, South Dakota, Utah, and Wyoming. Florida saw low rates at the beginning of COVID but experienced a sharp spike around week 18.

b. US State Policies:

This data set is provided by several research professors and students at Boston University including Julia Raifman et al. (2020). It covers the beginning dates for or existence of several popular nationwide policies. Some of these includes dates for: declaration of state emergency, announcement of stay-at-home order implementation and termination and/or relaxation, closing and reopening of: K-12 schools and daycares, non-essential businesses, restaurants excluding take-out, gyms, and movie theaters. Other independent variables include state demographics such as population density, population in 2018, homeless population in 2019, and percent of the state living under the federal poverty line in 2019. Data on racial disparities, incarcerated individuals, healthcare delivery, and quarantine and face mask rules is provided as well. This source also contains variables surrounding the expansion of unemployment benefit packages and insurance eligibility, which is what we are primarily interested in for this study.

We went through a process of aggregating the separate categorizing files into one data set. Then, we renamed and labeled all of the variables to be better formatted for analysis. We also reformatted the dates given for each policy to the DMY representation in order to match our other data sets for an easier merge. We dropped a myriad of variables that we deemed unnecessary for the regression we wanted to run. Table 2 shows..

Table 2- Proportion of States that implemented each policy

	Number of States that Implemented	Number of States that did not Implement	Total
UI EXTENSION TO QUARANTINED	42	9	51*
UI EXTENSION TO LOSS OF CHILDCARE	22	29	51
UI EXTENSION TO HIGH-RISK INDIVIDUALS	12	39	51
UI DURATION EXTENSION	4	47	51
STAY HOME MANDATE	40	11	51

Notes:
*District of Columbia is included as a state for this analysis
The quarantine policy typically recognizes immediate family members as sufficient individuals for benefit applications.
High-risk individuals include those with pre-existing health conditions and those over the age of sixty-five.
Individuals receiving benefits due to childcare loss typically have to be the primary caretaker for the household beyond that childcare substitute.

Next we created two categorical variables pertaining to stay-at-home policies. The first describes states that never implemented this mandate, states that implemented before and after the median date of implementation, March 28th, and states that terminated before and after the median date of termination, May 22nd. The second categorical variable pertains to timing of stay-at-home policies. This allows us to see effects of this mandate on unemployment before, during, and after implementation. Describe Table 3.

Table 3: Distribution of States by Timing of the Start and End of Stay-at-Home Mandate

	Ended Stay-at-Home mandate early	Ended Stay-at-Home mandate late
Adopted Stay-at-Home mandate early		
Adopted Stay-at-Home mandate later		
Never adopted such policy		

Table 2 identifies the number of states that implemented each of the unemployment insurance policies this research focuses on. As evidenced, most states extended eligibility of unemployment insurance to individuals who were quarantined or taking care of someone in quarantine. This policy had the highest rate of implementation of all six of the analyzed policies. States were more evenly split on their extension of unemployment insurance eligibility to individuals who had lost childcare or experienced school closures. Fewer states implemented policies that expanded insurance to high-risk individuals in preventative quarantine or extended the duration of time an individual can receive unemployment insurance. 40 states chose to implement a stay-at-home mandate. 24 states implemented this mandate before or on the median date of March 28, 2020, and 27 implemented this mandate after that median date. Conversely, 27 states terminated stay-at-home before the median date of May 22, 2020, and 24 states terminated the mandate on or after May 22, 2020. Some states chose to re-implement the stay-at-home policy later in 2020, but that data is not included in this analysis.

Table 4 - Summary Statistics

	MEAN	*STANDARD DEVIATION*	*MINIMUM*	*MAXIMUM*
POPULATION DENSITY 2018	392.64	1583.66	1.11	11496.81
HOMELESS PERCENTAGE 2019	8.47	1.16	6.31	11.93
UNEMPLOYMENT RATE 2018	4.75	1.05	2.80	7.50
PERCENT AT RISK FOR COVID	38.15	3.65	30	49.3

The percentage of a state population who is at risk of serious illness due to COVID are those with pre-existing health conditions or individuals over the age of 65. We can see that the mean age for this group is roughly thirty-eight years old. West Virginia is an outlier for percentage of population at risk for serious illness due to COVID with almost fifty-percent of their state population falling in this category. The natural log of state homelessness in 2019, which we use as another control variable, is also included in Table 4. While the average for this number is 8.47, California and New York have abnormally high rates at 11.93 and 11.43 respectively. States that have extremely high population densities—as of 2018—are Connecticut, D.C., Maryland, Massachusetts, New Jersey, and Rhode Island.

Figure 4- Date Distribution for Implementation of Stay-at-Home Mandates

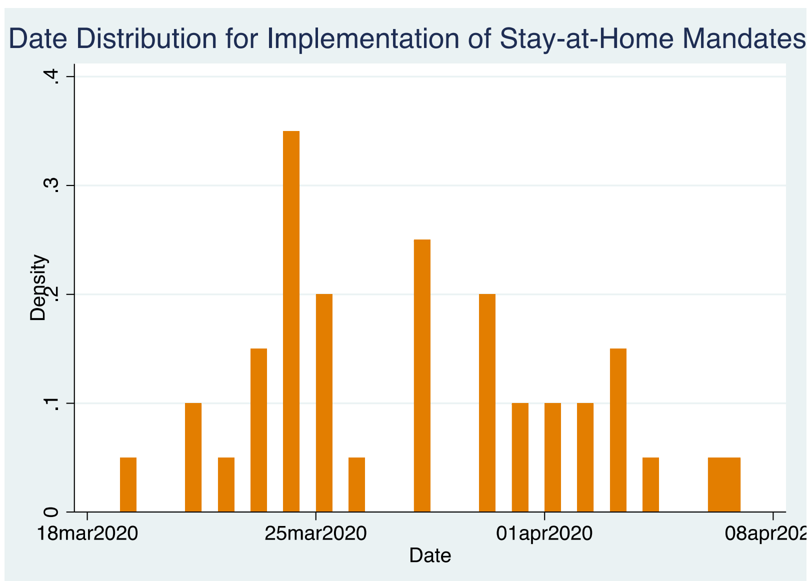
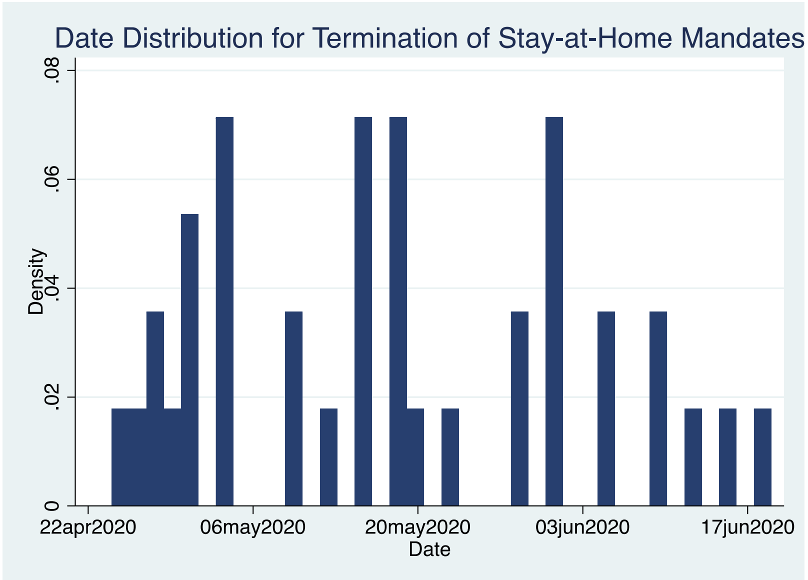


Figure 5- Date Distribution for Termination of Stay-at-Home Mandates



As evidenced in Figure 4, most states implemented a stay-at-home mandate between March 23rd and March 31st with the median date of March 28th, 2020. The earliest date for stay-home implementation was March 19th (California) and the latest was April 7th (South Carolina). The states that never implemented stay-at-home are Arkansas, Connecticut, Iowa, Kentucky, Nebraska, North Dakota, Oklahoma, South Dakota, Texas, Utah, and Wyoming. Most of these stay-at-home mandates were terminated or relaxed between May 1st and June 1st as seen in Figure 5. The earliest termination or relaxation of stay-at-home mandates was April 24th (Alaska) and the latest was June 19th (Oregon).

c. US COVID cases and deaths:

This data set uses state-level data to provide updates on the number of COVID cases and deaths daily. The data is part of an ongoing COVID Tracking Project, and is published by Deloitte and Datawheel ("Coronavirus Numbers By State"). It is updated at 4:00pm eastern time each day. Facets of this data set include cumulative positive and negative cases and tests per state, pending cases, cumulative hospital and ICU reports, and cumulative state deaths due to COVID.

In order to clean up this data, we first dropped entries whose dates were missing. We then reformatted the dates—which were originally given in YMD form—into MDY form to match the other data sets and be able to easily merge. We created a "cumulative tests" variable to represent both the positive and negative tests provided, and a "cumulative cases" variable to represent only positive tests. We then labeled specific variables including "test_cum", "cases_cum", and "deaths_cum". We dropped the state abbreviation "MP" which represents the Northern Marianas—a state we feel as though we didn't need for analysis. Our next task was to merge this data set with an existing one that allows for a quick conversion from state abbreviations to full state names using FIPS. This was necessary in order to merge this set with our other two sets whose state names are fully spelled out. Lastly, we dropped variables such as "dataqualitygrade", all of the ICU variables, all of the PCR test variables, the pending cases, the recovered cases, and the original date (because we had created a new formatted date variable).

Figure 6 - Log of Positive Cases by Week 2020

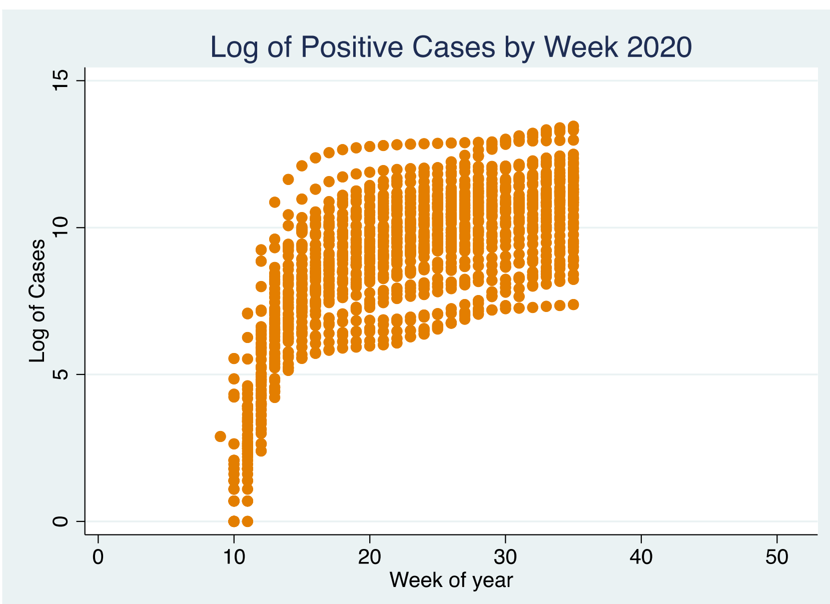
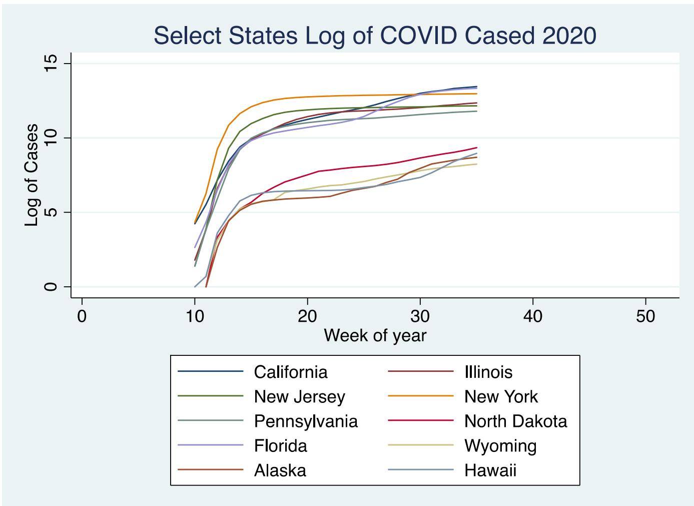


Figure 6 shows the log total number of cases in the U.S. this year. As evidenced, cases started to spike initially in week 12 and have been rising since—but at a slower rate. Figure 7 shows patterns of COVID spread for a select group of states that have had relatively high and low total cases. States with consistently low cases include Alaska, Hawaii, Maine, Montana, North Dakota, South Dakota, Vermont, West Virginia, and Wyoming. States with consistently high levels of cases are California, Illinois, New Jersey, New York, Pennsylvania, and Texas. Florida and Georgia saw sporadic spikes and drops in cases.

Figure 7 - Log of COVID Cases for Select States



V. Empirical Model

We use an (OLS) model to estimate the effect of various COVID-19 policies on the unemployment rate. This equation is used to estimate the effects of COVID-related variables, including policies in the year 2020 alone. The baseline equation and its components are given here:

Equation 1- Baseline 2020 COVID Spread and Policies

$$U_{iw} = \beta_0 + \beta_1 C_{iw} + \beta_2 P_{iw} + \beta_3 G_{iq} + \beta_4 X_i + \lambda_r + v_{it}$$

$\boldsymbol{U_{iw}}$ is the insured unemployment rate for state *i* in week *w*.

$\boldsymbol{C_{iw}}$ is the measure of the spread of COVID-19 (the log of total number of cases per thousand).

$\boldsymbol{P_{iw}}$ is a binary indicator for a given state policy after the time of implementation. This policy is the expansion of eligibility insurance to individuals in quarantine or taking care of someone in quarantine. Under the federally established CARES act, states were able to choose whether or not to allow for people who are quarantined or tending to someone in quarantine to apply for unemployment insurance, where they would typically not receive these benefits. Variations of this policy include someone who is in mandatory quarantine with suspicion of having COVID, someone who is quarantine because they are ill due to COVID, or someone who is caring for an "immediate family member." Because COVID spread is directly linked to necessary quarantining throughout a state, I hypothesize that as COVID cases rise and people are forced to be in quarantine at higher rates, more people will apply for unemployment insurance, therefore the insured unemployment rate will rise.

$\boldsymbol{G_{iq}}$ is the vector of control variables varying by quarter. These control variables include: economic growth (quarterly percent change in real GDP), personal income (log of per capita personal income), and GDP industry composition sectors such as manufacturing, retail and wholesale trade, healthcare, and food and accommodations. We've included only these control variables because they are reported in a very short time frame, and it is rare to have data reported so frequently. We chose to include these variables because they account for seasonal variation in unemployment before the onset of COVID. By controlling for this variation, our results will factor in existing unemployment effects do to state quarterly economic changes.

$\boldsymbol{X_i}$ is the vector of time-constant control variables prior to COVID-19. These include population density per square mile in 2018, homeless population in 2019, the insured unemployment rate in 2018, and the percent of people at risk for serious illness due to COVID (including pre-existing health conditions or over the age of sixty-five).

$\boldsymbol{\lambda_r}$ represents the five region fixed effects including the West, Midwest, Southwest, Northeast, and Southeast regions.

$\boldsymbol{v_{it}}$ is an error term capturing unobserved factors influencing unemployment rate. Examples of this include unobserved state demographics such as gender, race, ability, and age, as well as proportion of full-time and part-time workers. Demographics influence the unemployment rate because employment sectors are proportionally comprised of various genders, races, and ages, some of which experience higher rates of unemployment on average. This error term would also capture policies that we haven't explicitly included in our model such as face mask and quarantine mandates and closing of businesses. We assume that none of our independent variables are correlated with the error term.

A. Limitations to the Model

While we assume no collinearity or correlation between our independent variables and our error term, this assumption may be violated because of reverse causality. States with naturally high unemployment rates prior to COVID spread could implement these policies as a result of this high unemployment. This would confirm a correlation between these policies and the unemployment rate but in the opposite direction that we hope to argue in this study.

Our model also uses state-level data as the unit of analysis. This unit of observation has both positives and negatives. Our regression uses state-level data sets that are able to be easily merged, allowing us to view trends in the spread of COVID-19 cases, state policy changes, and unemployment rate fluctuations simultaneously. Most of these policies are introduced at the state level, however by using these data sets we are not able to observe more desegregate trends in the unemployment rate such as those at the county level. Our analysis also uses the insured unemployment rate instead of the true unemployment rate. This insured rate is an underestimation of true unemployment because the total number of people who are classified as unemployed do not apply for unemployment benefits, and are therefore not counted in the insured rate.

Another potential threat to the internal validity is that this model could be affected by is the time given for data collection or treatment. Because we are working on a short term, everchanging scale due to the volatility of COVID and COVID policy, the timeframe of our sample may be insufficient for proper analysis. Also, because this research focuses both on unemployment and a deadly, global pandemic, experimental mortality could be a serious threat to our research design and analysis. Ultimately, we recognize that there are a number of model limitations that we may not be able to account for.

B. Model Extensions

We estimate a similar model for each of the other four policies we are interested in. These policies include extension of unemployment insurance policies to high-risk individuals in preventative quarantine and individuals who have lost childcare or been affected by school closures due to COVID. Our last policy extends the duration of time an individual can receive unemployment benefits. High-risk individuals include those with pre-existing health conditions and those over the age of sixty-five. Individuals receiving benefits due to childcare loss typically have to be the primary caretaker for the household beyond that childcare substitute. Our model looks identical however our variable $\boldsymbol{P_{iw}}$ is now extended to encompass these three policies:

We hypothesize, in conjunction with our baseline quarantine policy model, that as COVID spreads and these policies are increasingly put into effect in various states to help with negative COVID externalities, unemployment insurance will be more accessible, therefore claims for unemployment benefits will rise. These policies are a direct effect of COVID, thus COVID is indirectly and directly linked to unemployment claims.

The next extension of our model takes into account the states that implemented stay-at-home mandates, whether these mandates were implemented and terminated "early" or "late", and if stay-at-home affected unemployment during the time it was in effect. We created a variable for stay-at-home categories including states that never implemented this mandate, states that implemented before and after the median date of implementation, March 28th, and states that terminated before and after the median date of termination, May 22nd. In this model extension we also include the categorical variable for before, after, and during implementation to highlight effects of the stay-at-home mandate at each phase of its path during COVID. $\boldsymbol{P_{iw}}$ is now extended to capture these stay-at-home categorical variables:

Equation 3 - 2020 COVID Stay-at-Home Policy Timing and Effects

$$U_{iw} = \beta_0 + \beta_1 C_{iw} + \beta_2 P_{iw} + \beta_3 G_{iq} + \beta_4 X_i + \lambda_r + v_{it}$$

We hypothesize that stay-at-home mandates due to COVID will have a significant effect on unemployment, both for the duration of the mandate and the timing of implementation and termination. States that had implemented before the median date and/or terminated after the median date will have higher unemployment rates than states that implemented after the median date and/or terminated before the median date. Also, the unemployment rate will be significantly higher during and after the presence of the mandate compared to before. We also predict that as cases grow, the effectiveness of stay-at-home mandates will decrease.

Our last model extension covers the three years prior to 2020, and it acts as a comparison for our 2020 COVID model. We then use this variated model to analyze the effects of our variables prior to COVID. This equation is very similar to our baseline, except it does not include any of the COVID-specific policy or case variables. We've also added variables for year fixed effects and month fixed effects to account for seasonality. This equation is:

Equation 4 – 2017-2019 Control Model

$$U_{iw} = \beta_0 + \beta_1 G_{iq} + \beta_2 X_i + \lambda_r + \theta_y + \delta_m + v_{it}$$

$\boldsymbol{\theta_y}$ is a set of year dummy variables or year fixed effects

$\boldsymbol{\delta_m}$ is a set of month dummy variables to account for seasonality

VI. Results

Based off Equations 1 and 2 in the Empirical Model section, we find the results given in Table 1.

Table 1- Effects of Policies on Unemployment

	POLICY	POLICY INTERACTION WITH CASE SPREAD
UI EXTENSION TO QUARANTINED	4.61**	-.41**
	(1.12)	(.11)
UI EXTENSION TO LOSS OF CHILDCARE	-0.25	0.08
	(.85)	(0.29)
UI EXTENSION TO HIGH-RISK INDIVIDUALS	-0.96	0.28*
	(.96)	(0.10)
UI DURATION EXTENSION	-6.42**	0.92**
	(1.71)	(0.18)

Notes:
Standard Errors are in parentheses
*significant at 10 percent level
**significant at 5 percent level

Table 2 identifies the results of each our regressions for the various policy binary indicators. The four policies of interest in this section are included in this table. Given these results, we can conclude that the expansion of unemployment insurance to those in quarantine and the extension of the amount of time an individual can receive unemployment insurance appear to have a statistically significant effect on the unemployment rate at the 5 percent level of significance. States that implemented extended eligibility of unemployment insurance to individuals in quarantine or taking care of someone in quarantine have a 4.6 percentage point higher rate of unemployment during COVID compared to states that did not implement that policy. States that extended the duration of time an individual can receive unemployment benefits during COVID have a 6.42 percentage point *lower* rate of unemployment than states that did not implement that policy.

While individuals may not have lost their jobs due to COVID spread, they may have been temporarily unable to perform those jobs in quarantine or while taking care of a close family member. As a result, some of these individuals applied for unemployment benefits. As COVID spreads and quarantine becomes increasingly more necessary, more people are likely to apply for unemployment benefits while in quarantine because it is an opportunity to recover money they would have lost due to temporary unemployment. We see this relationship in the higher rate of unemployment for states that implemented this policy.

The negative correlation between the policy extending the time an individual can be on unemployment benefits and respective unemployment rates for a given state is a bit more surprising. This may be a result of consistent unemployment in a state; for people who were already receiving unemployment benefits, the duration extension would not catalyze these individuals to start applying for benefits. Because the federally recognized state average maximum duration for benefits is 26 weeks (“Policy Basics,” 2020) and the fact that this study operates in a limited time-span, our research most likely misses some of the need for additional benefits. As COVID spreads and people are laid off or unable to work for more temporary periods of time, they most likely will be covered by the existing duration of insurance. Another explanation of this negative correlation could be reverse causality. States with generally high unemployment and higher rates prior to COVID might already have longer periods of time that people can receive benefits. Thus, these states may not have implemented duration extension policies, resulting in a negative correlation for states that did implement these policies and are seeing more claims for insurance than states with regularly high claims.

As part of our regression, we also included interaction variables to highlight the effectiveness of our policies in interaction with our number of cases, as seen in Table 1 as well. For our first policy, cases spread and unemployment benefits are negatively correlated. This relationship is unexpected, because we hypothesize that as cases grow, more people would be quarantined, thus more people would be claiming unemployment benefits for that quarantine. The relationship to case spread is positively correlated for our other three policies, which supports our hypothesis: as COVID spreads state-wide, more people would be inclined to apply for unemployment benefits. ***Not quite positive this is the right interpretation.

The results of our stay-at-home model extension are summarized below:

Table 2- Stay-at-Home Policy Effects

		Coefficient	*Interaction With Cases*
Stay Home Beginning	Late Implementation	0.39	-0.13**
		(0.66)	(0.064)
	Never Implemented	6.38**	
		(1.31)	
Stay Home End	Late Termination	-1.72**	0.30**
		(0.64)	(0.063)
	Never Terminated	-3.49**	
		(1.33)	
Stay Home Categories	During Policy	10.48**	-0.40**
		(0.66)	(0.08)
	After Policy	14.13**	
		(1.35)	

Notes:

Standard Errors are in parentheses
*significant at 10 percent level
**significant at 5 percent level

As evidenced in Table 2, states that implemented stay-at-home mandates after the median date of March 28th, compared to states that implemented before that date, have not seen a significant effect on unemployment rates. However, there is a significant effect for states that implemented stay-at-home mandates versus those who didn't. States that did implement, at any point during 2020, have a 6.38 percentage point lower unemployment rate than states that did not implement. This does not concur with Béland et al.'s results for stay-at-home or our hypothesized results. This could be due to heterogeneity; states that didn't implement stay-at-home could have lower cases of COVID and simultaneously lower unemployment due to lower rates of health effects that case spread has on unemployment. Thus, states that did implement stay-at-home naturally also might have had higher unemployment than those who did not. When we control for this interaction between COVID spread and unemployment, we can see that states that did implement and implemented before March 28th actually have .13 percentage point higher unemployment than states who never did so or did so late. Also seen in Table 2: states that terminated stay-at-home mandates after the median date of May 22nd, have a 1.72 percentage point lower unemployment rate than those who terminated early. These results could follow our explanation of heterogeneity. When we account for interaction with COVID spread and the effectiveness of this policy with cases, states that terminated late have a .30 percentage point higher unemployment rate.

Lastly, Table 2 describes the effects of the categorical variable for stay-at-home before, during, and after the presence of the mandate. While stay-at-home was in place, states that implemented had a 10.48 percentage point higher rate of unemployment than before the mandate was in place. After the policy was terminated, states that had implemented stay-at-home had a 14.1 percentage point higher rate than before the states had put this policy into effect. This follows with our hypothesis and with prior studies, that COVID stay-at-home mandates increased unemployment. This could be a result of businesses closing, people's inability to go into work, etc. The interaction variable between stay-at-home categories and the spread of COVID is -0.40. We would expect this negative correlation because we hypothesized that as cases grow, policy becomes increasingly less effective.

Table 3- Previous Years vs. Current Year Model

	2017-2019 MODEL	2020 MODEL
ECONOMIC GROWTH	-0.02**	-0.99**
	(0.00)	(0.09)
PERSONAL INCOME PER CAPITA	1.15**	6.67**
	(0.07)	(0.95)
MANUFACTURING SHARE OF GDP	0.01**	0.21
	(0.00)	(0.02)
TRADE SHARE OF GDP	-0.06**	-0.16**
	(0.00)	(0.04)
HEALTHCARE SHARE OF GDP	0.10**	0.14**
	(0.00)	(0.07)
FOOD/ACCOMODATIONS SHARE OF GDP	-0.02**	0.33**
	(0.00)	(0.07)
REGION:		

MIDWEST	-0.47**	-0.27
	(0.02)	(0.26)
SOUTHWEST	-0.23**	1.42**
	(0.03)	(0.37)
NORTHEAST	-0.23**	-0.20
	(0.03)	(0.33)
SOUTHEAST	-0.46**	0.28
	(0.02)	(0.27)

Table 3 shows our control variables that vary by quarter as well as our region categorical variables for our previous years and current year model. Overall, most of the variables seem to have a greater effect on unemployment in 2020 than they did in previous years. This may be because our economy looked different in the years leading up to 2020 than it did this year. The Trump administration can be partly credited with unemployment and poverty declines, wage increases, tax cuts, and federal regulation reforms during the period between inauguration and 2019. However, according to Lemieux (n.d.) even before COVID struck, some of these regulations such as net-neutrality, changes in health insurance policies, “joint employer” policies, and restrictions on imported goods set the U.S. up poorly for the economic shock that has now hit America hard (Lemieux, n.d.)). Because of the long-term trends from these introduced regulations, our economy may have looked different this year than in the years leading up to it.

One interesting thing to note is that the retail trade sector of GDP has a negative effect on unemployment in both models. This could be due to the volatility of the some of the other industry sectors (manufacturing, healthcare, food and accommodations) or the fact that some retail trade goods are inferior goods. A higher share of trade could also mean more businesses staying open, leading to lower unemployment. For our 2020 model, consumption for businesses like clothing, home goods, and grocery stores increased—most likely offsetting COVID unemployment effects. Another notable result is the region fixed effects. Each region in our 2017-2019 model decreased unemployment relative to the West region. However, in our current model, states in the Southwest region have a 1.42 percentage point higher unemployment than the West region. This may be due to the Southwest relying heavily on the food/accommodation sector and quarrying oil and natural gas, both industries for which COVID shutdowns and cautions had large effects (Diment et al. 2016). While the West generally has trending high unemployment, it seems as though other regions may have been more strongly affected by the repercussions of COVID this year.

VII. Conclusions

As this paper has highlighted, states' decisions to implement unemployment insurance expansion policies, as a response to COVID labor market destruction, has resulted in more unemployment benefit claims and higher insured unemployment rates. Several of these expansion policies had significant effects on unemployment such as extension to those in quarantine, longer duration one can receive benefits, and the timing and implementation of stay-at-home mandates. While this study contributes to the existing research on unemployment policies and stay-at-home effects, there is still much research to be done on labor market destruction as a result of COVID. Further research can look into the long-term effects of these expansion policies, and the second implementation of stay-at-home mandates that some states chose to effect. These policies were studied in an abnormal, time-sensitive, and extreme scenario. It may be beneficial to study the effects of these policies in a less volatile economic setting. Our research suggests that these policies are somewhat significant and helpful in response to COVID externalities, thus we advise that states consider maintaining some of these policies through the end of the year, at least.

VIII. Appendix:

Further Description of All Variables Used in our Regression:

1. Unemployment Rate: the insured unemployment for a given state at a given date. This rate is equal to the number of people currently receiving unemployment as a percentage of the labor force. These rates are updated on a weekly basis.
2. Cases: the measure of the spread of COVID-19 (the log of total number of cases per thousand). This is a measure of case spread by state, and these numbers are updated on a daily basis at 4 pm Eastern time.
3. UI Extension to Quarantine: Expansion of eligibility of UI to anyone who is quarantined and/or taking care of someone who is quarantined. This typically applies to oneself an close family members.
4. UI Extension to Loss of Childcare: Expansion of eligibility of UI to those who have lost childcare/school closures. The individual receiving this insurance has to be the primary caretaker of the children second to the lost childcare substitute.
5. UI Extension to High-Risk Individuals: Expansion of eligibility to high-risk individuals in preventative quarantine. “High-risk individuals” describes people with pre-existing health conditions or those over the age of 65.

6. UI Duration Extension: Extension of the amount of time an individual can be on UI past a given state's regular maximum number of weeks.
7. Stay Home Begin: a categorical variable for the timing of implementation of stay-at-home mandates. "Early" describes implementation before the median date of March 28, 2020. "Late" describes implementation after this date. "Never" describes states that never implemented this mandate.
8. Stay Home End: a categorical variable for the timing of termination or relaxation of stay-at-home mandates. "Early" describes termination before the median date of May 22, 2020. "Late" describes implementation after this date. "Never" describes states that never implemented, thus never terminated, this mandate.
9. Stay Home Category: a categorical variable for the time-varying effects of this policy. "Before" describes the effects of stay-at-home policy prior to the mandate. "During" describes effects of the policy while the mandate was in effect. "After" describes the effects after the mandate had been terminated.
10. Economic Growth: Quarterly percent change in real GDP from preceding period (annualized) in millions of chained 2012 dollars.
11. Personal Income: per capita personal income. Total personal income divided by total quarterly population estimates in millions of dollars—seasonally adjusted at annual rates.
12. Manufacturing Share of GDP: the percent contribution of manufacturing in GDP by state. Created by dividing the total quarterly GDP in dollars by the total quarterly GDP in dollars in the manufacturing industry for a given state in a given quarter.

13. Trade Share of GDP: the percent contribution of trade in GDP. Created by dividing the total quarterly GDP in dollars by the total quarterly GDP in dollars in the trade (retail or wholesale) industry for a given state in a given quarter.

14. Healthcare Share of GDP: the percent contribution of healthcare and social assistance in GDP. Created by dividing the total quarterly GDP in dollars by the total quarterly GDP in dollars in the healthcare and social assistance industry for a given state in a given quarter.

15. Food and Accommodations Share of GDP: the percent contribution of accommodation and food services in GDP. Created by dividing the total quarterly GDP in dollars by the total quarterly GDP in dollars in the accommodation and food industry for a given state in a given quarter.

16. Population Density 2018: population density per square miles in 2018 per respective state.

17. Homeless Percentage 2019: percent of people who were homeless in 2019 for a given state.

18. Unemployment Rate 2018: percent of people who were unemployed in 2018 for a given state.

19. Percent at Risk for COVID: percent at risk for serious illness due to COVID. These people have pre-existing health conditions or are over the age of 65.

20. Region: categorical variable for state by each region (West, Midwest, Southwest, Northeast, and Southeast) as defined by the National geographic.

21. Year: a year categorical variable for year fixed effects.

22. Month: a month categorical variable to account for seasonality.

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