The Effect of the COVID-19 Pandemic on the US Economy

by

Benjamin Chang

Submitted March 21, 2021

STAT 222: Masters of Statistics Capstone Project

Introduction & Objective

The coronavirus disease 2019 (COVID-19) originated in Wuhan, China in December 2019 and has spread throughout the world since. Because of the number of lives the virus has taken and the contagiousness, the United States began to impose public health policies to contain the virus where they limited people traveling and required citizens to wear personal protective equipment. The federal government let states implement health policies on their own so as a result, some states were stricter, and some were more lenient. Regardless, the health policies caused the mobility of people to decrease as people could not travel as freely as before and as a result, areas such as workplaces and retail saw a decrease in people [4]. As a side effect, businesses began to struggle because of the sudden decrease in consumers buying goods and there was a massive layoff soon after. The decrease in business across industries led to a spike in the unemployment rate around March 2020. Since then, the unemployment rate has improved, but never returned to normal due to ongoing health restrictions due to the COVID-19 pandemic.

As a result, the question that our team wanted to pose is how much the COVID-19 pandemic affected the U.S. economy. For the sake of this project, we decided to concentrate on the change in the unemployment rate due to the limited time frame in exploring this phenomenon. The change in the unemployment rate will vary on the variables mentioned above where states implementing varying stringency for health policies will influence the change in mobility. As a result, the change in mobility will affect the amount of business received in different industries.

Literature Review & Methods

Before obtaining data, some literature review was conducted to get more information on what variables affected the unemployment rate during the COVID-19 pandemic. In Baek. Et al. (2020) [1], the main variable that was considered when trying to model the unemployment insurance claims is the length of stay-at-home order by state and time. There was a control variable that took account of the severity of local exposure to COVID-19 within states. From the paper, it was noted that an additional week of stay-at-home exposure increased a state’s weekly initial unemployment insurance claim by 1.9% of its employment level relative to other states. This implies there is an effect of how early the government imposes health stringency laws and the unemployment insurance claims. Therefore, it was noted to consider the stringency of each state’s health policies in our model.

There are some limitations of the literature that could be further investigated in our study. There was a narrow time frame that was studied in Baek. Et al. (2020), and with more data accessible since the paper was published, we can gather more data and fit a more accurate model. Also, the study only considered stay-at-home orders in modeling the unemployment rate, but more variables should be considered for a more accurate model. From noting the literature, we can determine that other variables can affect the unemployment rate. The stringency of each state's policies will have a huge effect on people going to common areas such as retail and residential areas, so determining the change in the number of people before and during the pandemic might influence businesses. Implementing mobility restrictions in a certain area will affect certain businesses more than others. For example, a souvenir shop in a tourist destination will see a larger decrease in business compared to big tech companies, whose business relies on web services.

From reasoning possible variables to input into our model, we decided to use the following equation as our initial time series model for the unemployment rate:

$$\Delta UR_{s,t} = \alpha + \beta * \Delta Mobility_{s,t} + \gamma * \Delta Stringency_{s,t} + \delta * sector_{s,t} + \theta * \left(\Delta Mobility_{s,t} * sector_{s,t}\right) + \rho * \left(\Delta Mobility_{s,t} * \Delta Stringency_{s,t}\right) + \mu_s + \pi_t + \epsilon_{s,t} \quad (1)$$

where $\Delta UR_{s,t}$ is the change in the unemployment rate by state and time, μ_s is the state fixed effect, π_t is the time fixed effect, β, γ, δ, θ, ρ, are the coefficients for the corresponding independent variables, and $\epsilon_{s,t}$ is the residual error.

The change in the unemployment rate is our target variable to normalize the unemployment rate over time. Since different states have varying stringent health policies, we took into consideration that the different levels of stringency will affect other variables, so an interaction term was considered between mobility and stringency. Likewise, the change in mobility will have an impact on the sector and the unemployment rate so another interaction term was created in the model. The time fixed effect and state fixed effect were included in the model to offset any unobserved heterogeneity.

Data Description

To help determine the coefficients of each variable, the Google Mobility dataset, the unemployment dataset, and the stringency of COVID-19 policies by state dataset were used. Since obtaining the seasonally adjusted data was not feasible for all datasets, we decided to only use non-seasonally adjusted data.

The Google Mobility dataset was considered to determine the change in mobility for different categories of places such as parks and retail. Google obtains their mobility data from people's location history from their phones, but bias can be induced into the data if people decide to turn off their location history, which can be common for people concerned with privacy. The change in mobility is calculated by taking the number of visitors in the categorized place and subtracting it from the baseline day, which is calculated from taking the median mobility for the day of the week in a 5-week period between January 3rd, 2020, and February 6th, 2020 [4]. There is one observation for the mobility per day and for the scope of our analysis, we decided to only look at the retail mobility.

Datasets that contain the unemployment rate by state and sector were obtained from the U.S. Bureau of Labor Statistics. The datasets contain the unemployment rate for a particular month. The unemployment rate was determined by taking the number of unemployed people divided by the total labor force. This was obtained by a monthly survey by the federal government called the Current Population Survey (CPS) where there are 60,000 eligible households surveyed from approximately 2,000 geographic areas [3]. From that, they calculated the unemployment rate for the sample and then generalized it for the current population. These datasets which contain the unemployment rate by state and sector are essential to our study as the unemployment rate is our main variable of interest to determine how much businesses are affected by the COVID-19 pandemic. Having different unemployment rates by state and sectors will help us further investigate the relation between the variables in our model.

An example of the data in the Google Mobility and unemployment dataset is illustrated in **Figure 1** in the Appendix, where for the state of California, the unemployment rate and change in mobility are plotted over time. The retail mobility sharply decreased in March 2020 and then never recovered to normal, which is inversely related to the unemployment rate where the unemployment rate spiked in April 2020, suggesting that there might be a correlation to further investigate.

The last dataset that was considered was the U.S State Stringency COVID-19 Policies dataset, which came from the University of Oxford School of Government [2]. The dataset is updated daily by a group of over 100 Oxford students, alumni, staff, and project partners to assess the current health policies. The stringency of a state is calculated by 9 different response indicators shown in **Table 1** of the Appendix. From the 9 different indicators, the stringency index is calculated the following way:

$$stringency\ index = \frac{1}{k}\sum_{j=1}^{k} I_j \tag{2}$$

where I_j is the sub-index score and k is the number of response indicators. The dataset will be used in our modeling by considering the change in stringency throughout the whole pandemic to see if there is an effect on the unemployment rate.

An example of the data in the U.S State Stringency COVID-19 Policies dataset is illustrated in **Figure 2** in the Appendix, where the stringency index is plotted over time for the state of California. The stringency index sharply increased in March 2020, almost the same time that the mobility decreased, which implies possible causation between the stringency index and the mobility.

Results & Discussion

From doing exploratory data analysis, we determined from **Figures 3 and 4** in the Appendix that the stringency index varies between states. The category of the state is divided by its governor's political party affiliation. It can be noted that the states that are affiliated with the Republican political party on average have a lower stringency index than states affiliated with the Democratic political party and therefore, this causes the change in the average retail mobility to be lower.

The next relation that was considered was the effect of the change in mobility on the change of the unemployment rate for each sector. **Figure 5** illustrates the effect of the change in the unemployment rate on the change in mobility in the leisure and construction industry.

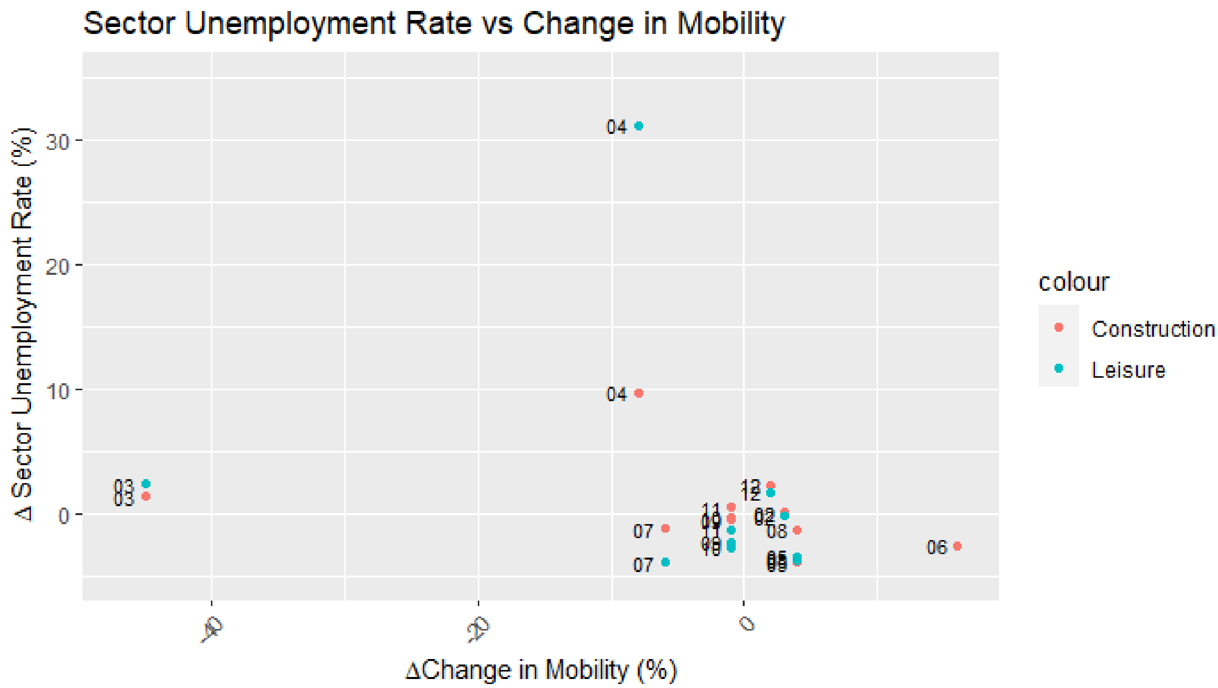

Figure 5: Plot of Change in Unemployment Rate on Change in Mobility

In the plot, the change in mobility is the same between the two sectors due to not finding data that relates the mobility to each sector. It is noted in the plot that there is a massive difference in the change in the unemployment rate during April 2020 between the leisure and construction industry. For all the other months, there is a difference of less than 5% between the two industries. However, these variances of change in the unemployment rate between the two sectors over time will help vary δ in our model, which helps determine the significance of the sector parameter in our model.

Next, we wanted to see how the change in mobility effects the unemployment rate within each state. **Figure 6** illustrates the effect of the change in the unemployment rate on the change in mobility for a couple of states.

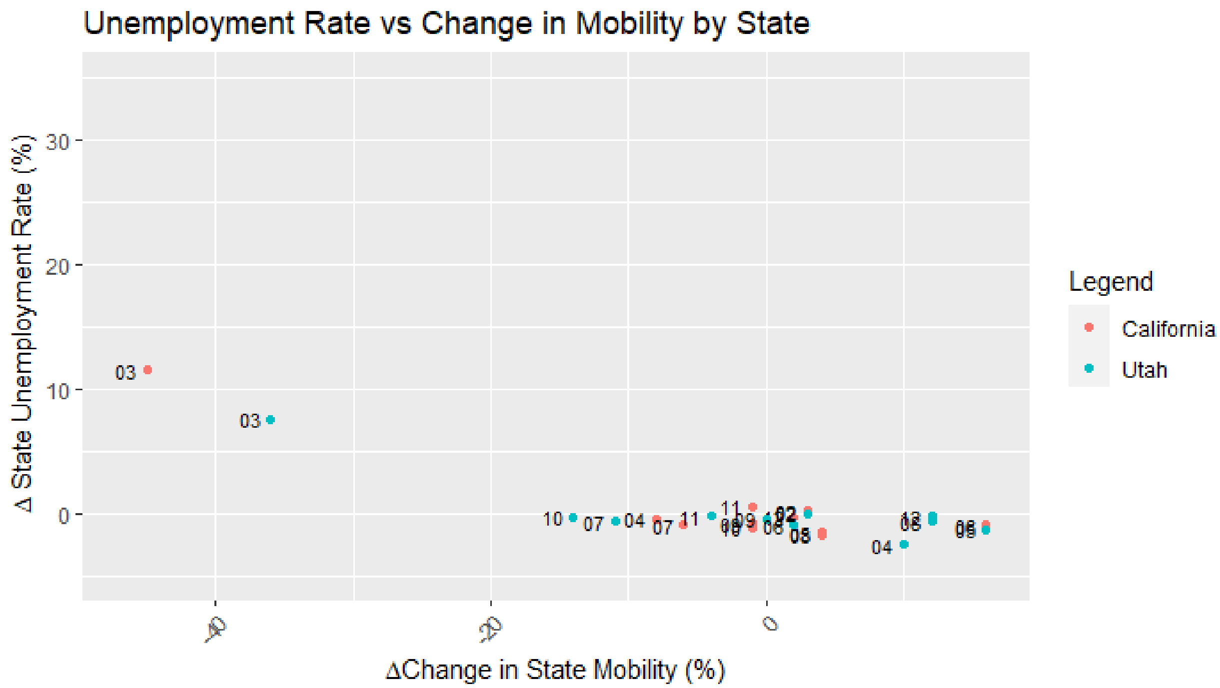

Figure 6: Plot of Change in Unemployment Rate over Change in Mobility per State

California and Utah were chosen because California is traditionally a democratic state while Utah is a republican state, which implies from an earlier analysis that their stringency of health orders will be different and in turn, have varying mobility. There seems to be a significant difference in the change in mobility and the unemployment rate between California and Utah during March 2020. However, for all the other months, there does not seem to be a significant difference in the change in the unemployment rate for varying changes in mobility. This suggests that the change in mobility variable will not have a large effect on the change in unemployment. The β coefficient as a result is expected to not have a large magnitude compared to the other coefficients.

Lastly, the change in stringency was compared to the change in the unemployment rate within each state. **Figure 7** illustrates the change in stringency versus the change in unemployment rate for California and Utah.

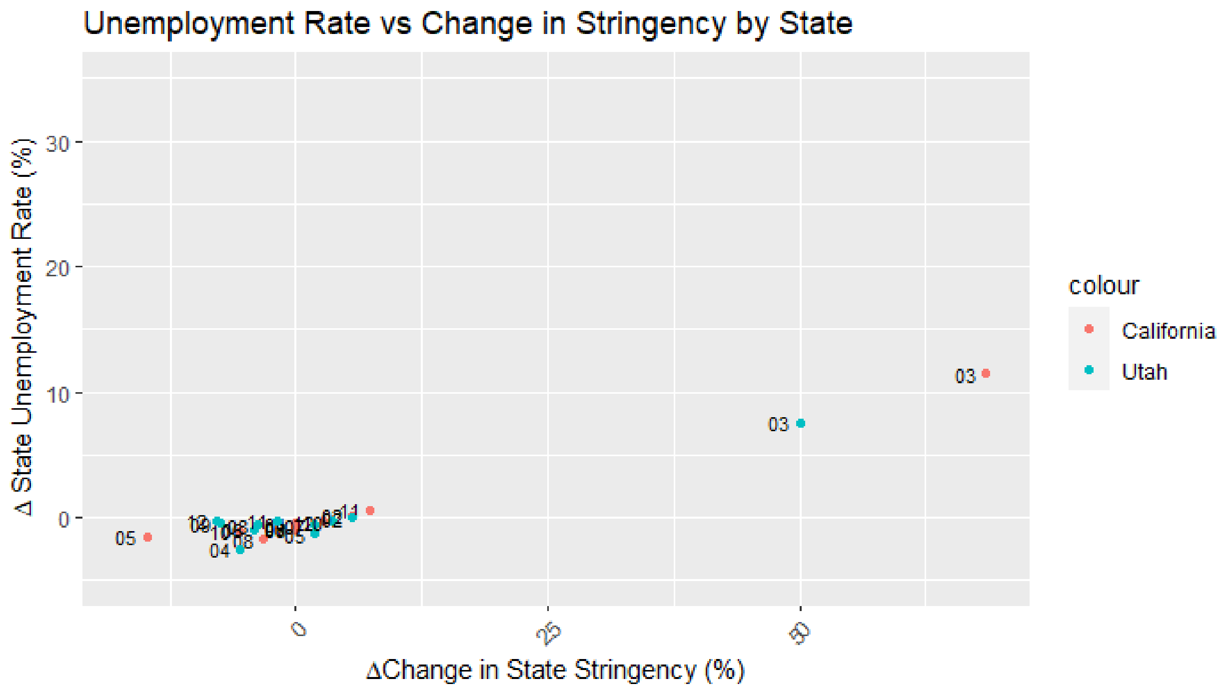

Figure 7: Plot of Change in Unemployment Rate on Change in Stringency per State

It is noted that there is a lot of points bunched up when the change in stringency is zero, which is expected since there is a huge plateau in **Figure 2** followed by minor changes. Like all other variables explored, the difference in the state stringency in March 2020 is significant and will greatly contribute to the magnitude of the γ coefficient.

Conclusion & Future Work

From our results, we conclude that there is a significant difference in the change in stringency and change in mobility between states during March 2020. This will likely differentiate the states and be a significant factor of the magnitude of the γ and β coefficients in our model. The sector unemployment rate varied between each sector, especially during April 2020, when layoffs were massive shortly after the health orders. This will largely contribute to the magnitude of δ in our model.

For our future work, we will need to further explore the interaction terms that were not analyzed in this report. After doing so, we plan to fit the model with our data and see the magnitude of the coefficient matches our analysis in this report. We also will run residual analysis and take note of the error between our data and model. From there, we can tune our parameters so that the model will better fit our data. After we obtain the parameters and the coefficients for our model, we plan to use statistical inference to determine the causal relation and magnitude of the effect between each of the independent variables and the unemployment rate. By determining the relationship between the independent variables and dependent variables, we can better inform the government and economists of how the magnitude of the change in one of our independent variables will end up affecting the unemployment rate.

References

1. Baek, ChaeWon, et al. "Unemployment Effects of Stay-at-Home Orders: Evidence from High Frequency Claims Data." *The Review of Economics and Statistics*, 2020, pp. 1–72., doi:10.1162/rest_a_00996.

2. "COVID-19 Government Response Tracker." *Blavatnik School of Government*, Mar. 2020, www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker.

3. "How the Government Measures Unemployment." *U.S. Bureau of Labor Statistics*, U.S. Bureau of Labor Statistics, 8 Oct. 2015, www.bls.gov/cps/cps_htgm.htm.

4. "Overview - Community Mobility Reports Help." *Google*, Google, support.google.com/covid19-mobility/answer/9824897?hl=en&ref_topic=9822927.

Appendix

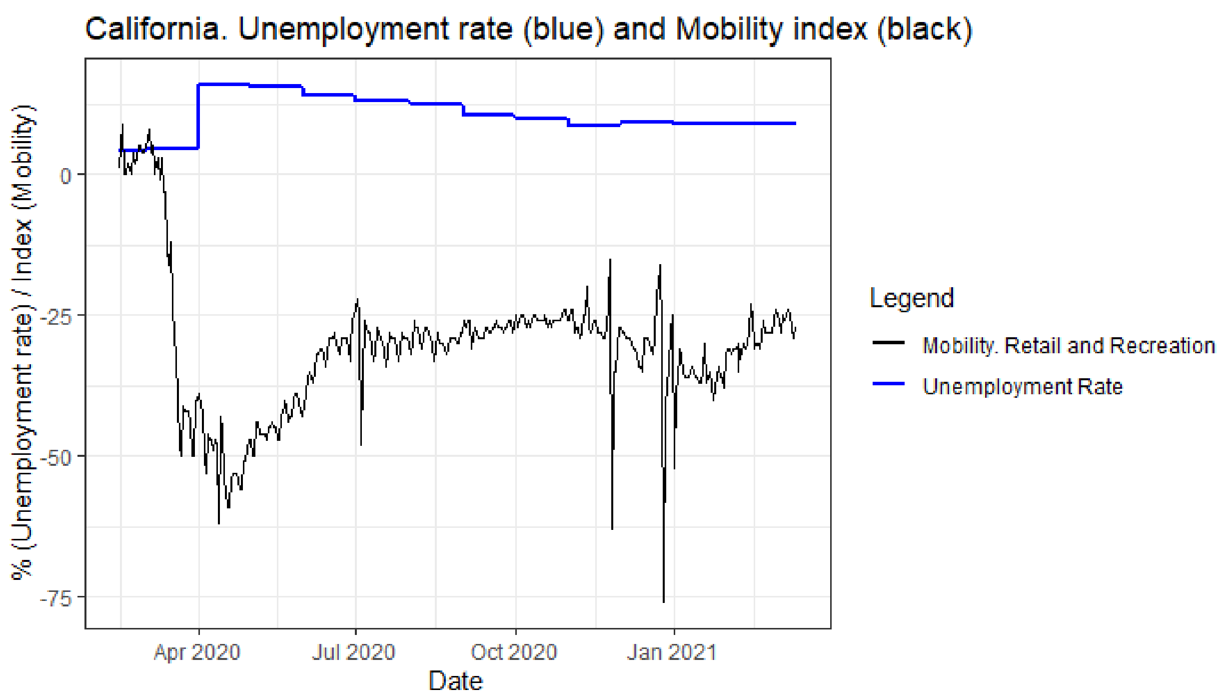

Figure 1: Plot of Unemployment Rate and Mobility Index over Time (California)

Table 1: The Individual Indicators which make up the Stringency Index

Name	Type	Max Value
School Closing	Ordinal	3 (0, 1, 2, 3)
Workplace Closing	Ordinal	3 (0, 1, 2, 3)
Cancel Public Event	Ordinal	2 (0, 1, 2)
Restrictions on Gathering Size	Ordinal	4 (0, 1, 2, 3, 4)
Close Public Transport	Ordinal	2 (0, 1, 2)
Stay at Home Requirements	Ordinal	3 (0, 1, 2, 3)
Restrictions on Internal Movement	Ordinal	2 (0, 1, 2)
Restrictions on International Travel	Ordinal	4 (0, 1, 2, 3, 4)
Public Information Campaign	Ordinal	2 (0, 1, 2)

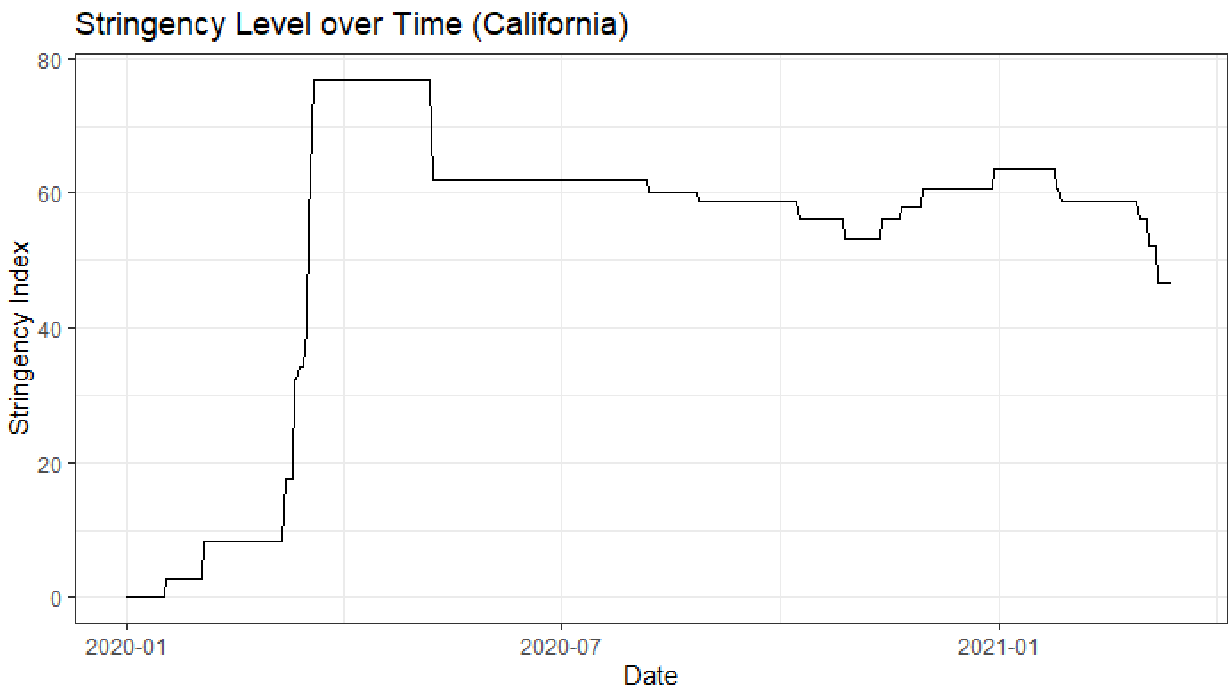

Figure 2: Plot of Stringency Index over Time (California)

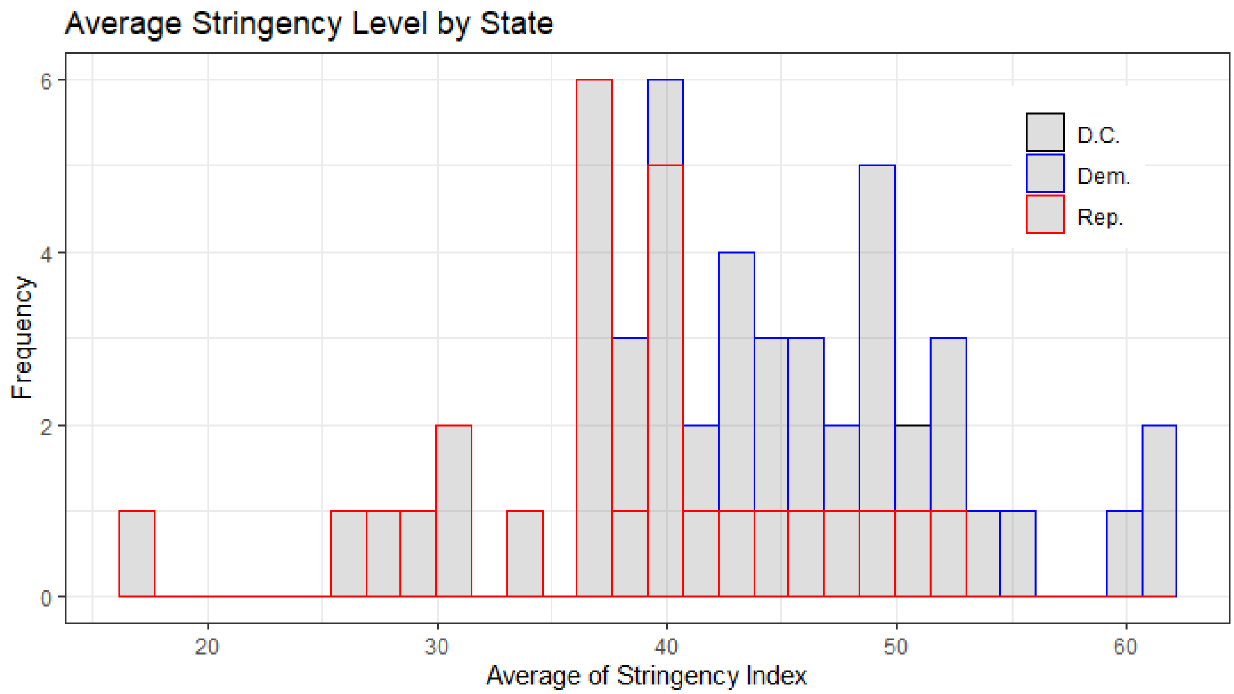

Figure 3: Plot of Stringency Index by State (Political Party)

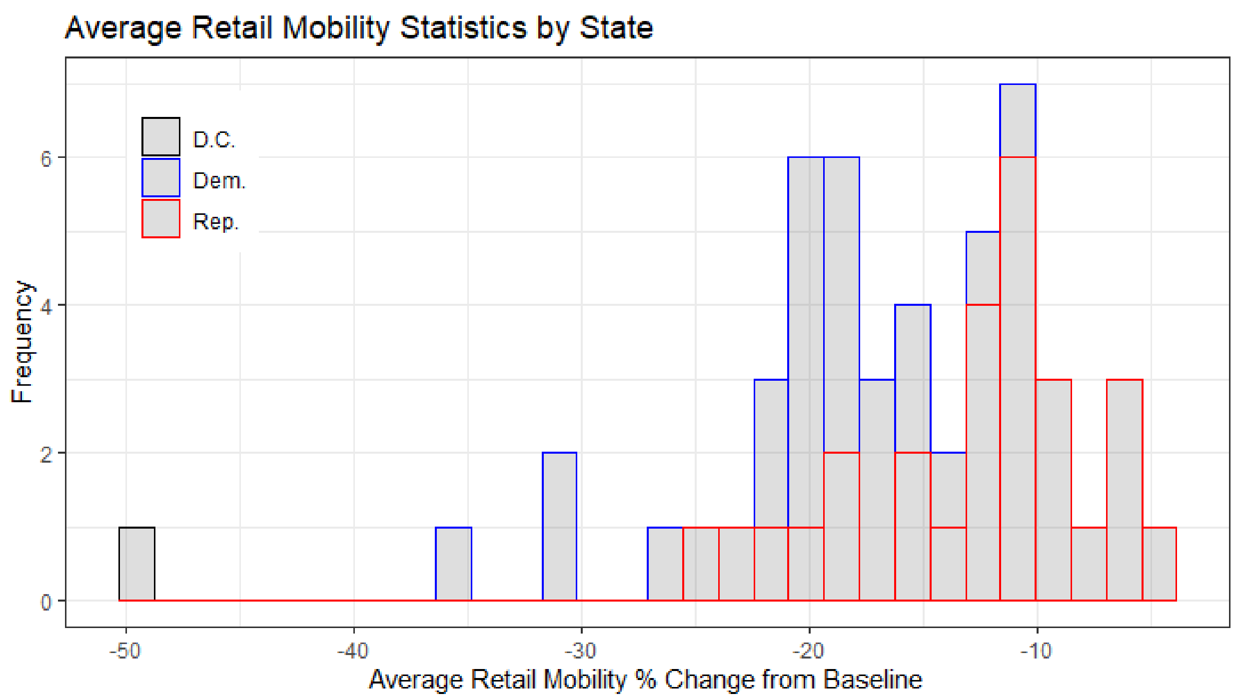

Figure 4: Plot of Retail Mobility by State (Political Party)