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

by

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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 employment rate around April 2020. Since then, the employment 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. After that, we want to use the obtained model to predict the employment rate for February 2021. For the sake of this project, we decided to concentrate on the change in the employment rate due to the limited time frame in exploring this phenomenon. The change in the employment 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 employment rate during the COVID-19 pandemic. In Baek. Et al. (2020) [1], the main variable that was considered when trying to model the employment 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 employment 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 employment 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 employment 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 employment rate. 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 employment rate:

$$\%\Delta Emp_{s,t,sec} = \alpha + \beta_1 * f_{sec}(\%\Delta Mobility_{s,t}) + \beta_2 * \Delta Stringency_{s,t} + \beta_3 * Sector_{s,t} * f_{sec}(\%\Delta Mobility_{s,t}) + \beta_4 * (Sector_{s,t} * \Delta Stringency_{s,t}) + \mu_{sec} + X_{s,t} * \Gamma + \epsilon_{s,t,sec} \quad (1)$$

where $\%\Delta Emp_{s,t,sec}$ is the change in the employment rate by state and time, μ_{sec} is the sector fixed effect, $X_{s,t}$ are the time and state fixed effect, β_1, β_2, β_3, β_4, and Γ are the coefficients for the corresponding independent variables, and $\epsilon_{s,t,sec}$ is the residual error.

The change in the employment rate is our target variable to normalize the employment 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 sector and stringency. Likewise, the change in mobility will have an impact on the sector and the employment 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.

Since we have more data to use to fit our model, this creates a problem where only the 2nd quarter of 2020 contains the months where employment significantly changed. Fitting the whole data to one single model would produce an inaccurate representation of the spike in the 2nd quarter of 2020. Therefore, to alleviate this problem, we decided to fit the data from the 2nd quarter of 2020 to the model, and then fit all the other data to another model to obtain separate coefficients. When fitting the data from the 2nd quarter of 2020, this will be regarded as a period where there is panic and there is a sharp change in employment; on the contrary, the data not pertaining to the 2nd quarter of 2020 will correspond to the model where there is no panic and there is an insignificant change in employment.

The function $f_{sec}(\%\Delta Mobility_{s,t})$ was considered within our model because the best fit curve for different sectors had different patterns when seeing a relationship between mobility and change in employment. For example, the data regarding the leisure and hospitality industry in the 2nd quarter of 2020 cannot be fit using a linear model as depicted in **Figure 1** in the Appendix. Therefore, a sigmoid function was used to better represent the data. For all the other industries, a linear model was able to be used to represent the data.

Data Description

To help determine the coefficients of each variable, the Google Mobility dataset, the employment 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 residential mobility.

Datasets that contain the employment rate by state and sector were obtained from the U.S. Bureau of Labor Statistics. The datasets contain the employment rate for a particular month. The employment rate was determined by taking the number of employed 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 employment rate for the sample and then generalized it for the current population. These datasets which contain the employment rate by state and sector are essential to our study as the employment rate is our main variable of interest to determine how much businesses are affected by the COVID-19 pandemic. Having different employment 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 employment dataset is illustrated in **Figure 2** in the Appendix, where for the state of California, the employment 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 employment rate where the employment 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 employment rate.

An example of the data in the U.S State Stringency COVID-19 Policies dataset is illustrated in **Figure 3** 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 4 and 5** 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. However, other confounding variables were not considered such as the difference in the sentiment of business owners in states affiliated with the Democratic or Republican political party. Some owners might think that COVID-19 is serious and lay off more people in Democratic states versus in Republican states where COVID-19 is not perceived as a serious threat. Therefore, we decided that the time fixed effect, Γ, will capture these trends.

Table 2 in the Appendix depicts the regression results and coefficients after fitting our model to the data pertaining to the 2nd quarter of 2020. It is noted that the R^2 of the fit is 0.675, which implies that the model is a relatively good fit for the data. When looking at the t-test results for both the variables and interaction terms, it is noted that almost all the variables produced significant results. **Table 3** in the Appendix depicts the regression results and coefficients after fitting our model to the data pertaining to all the other data not pertaining to the 2nd quarter of 2020. The R^2 of the model is 0.139, which is a bad fit for the model. This is reflected when we look at the t-test and see that only a handful of the variables are significant in the fit. This might happen because since there is a relatively low change in employment, there might not be a strong correlation between the variables and the change in employment. The pattern in the change in employment is not as pronounced as the data from the 2nd quarter of 2020.

Next, we want to determine which variables are the most important when measuring the change in employment. To determine this, we used a random forest regression classifier and fitted the data against our model. After fitting the model to the data, we can obtain the importance of each variable relative to the change in employment. Some of the criteria include a high information gain using each variable, frequency of a variable occurring within a decision tree, and if the variable occurs in many different decision trees. **Figure 6** in the Appendix depicts the feature importance for the data pertaining to the 2nd quarter of 2020. It is inferred from the plot that mobility was the most important factor in the change in employment, followed by the leisure and hospitality sector. This implies that a change in mobility will greatly impact employment rates in a future pandemic. This ties into the second most important variable, the leisure and hospitality industry, where the industry is highly dependent on foot traffic. We can conclude that a lack of mobility of people will hinder a country's economy. **Figure 7** in the Appendix depicts the same pattern even in the time when there is no panic. The mobility and leisure and hospitality industry are the most important features, which suggests that even when we are in a pandemic and people are not panicking, foot traffic impacts the economy from the variables that we analyzed.

In addition to finding the most important variables, we want to use our models to make predictions for future data. When using February 2021 data to predict the change in employment, we obtain the results in **Figures 8 and 9** of the Appendix, which depicts the predicted change in employment versus the actual change in employment. From the plots, we can conclude that the predictions from the data regarding the 2nd quarter of 2020 are not accurate, while the predictions from all the other data are moderately accurate. The RMSE is the fit of the model from the 2nd quarter of 2020 was 9.4% while the model using all the other data had an RMSE of 1.95%. Since in February 2021 there was not much panic occurring in the population, it is expected that the model that was fitting using the 2nd quarter of 2020 data did not perform well because there was panic occurring. On the contrary, the model was a good fit for the data where there was not much panic in society. We would need another wave of COVID-19 cases and deaths to fully test the model regarding a panic sentiment and see how that portion of the pandemic truly affects the economy.

Conclusion

From our results, we conclude that the most important variables when considering the change in employment are mobility and the leisure and hospitality industry. This implies from our model that β_1 has a significant impact in determining the change in employment. β_3 has a large impact only when the sector is leisure and hospitality. When using our model created from all other data not related to the 2nd quarter of 2020, we find that there is a moderate fit to the data when predicting the change in employment rate in February 2021; future data is needed to determine if the model derived from the 2nd quarter of 2020 data accurately reflects times where there is a panic sentiment.

One improvement that can be made in this analysis is to keep improving the model as there is more data regarding the COVID-19 pandemic. As more data is available to analyze, this can help fine-tune our model and give a better representation of the data, which can lead to more accurate inference and prediction. Another improvement that can be done is to incorporate the state variable into the model and see if there are any improvements in inference and prediction. From creating our models and analyzing the important 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. These valuable insights can help the government prepare for situations like COVID-19 when there is a panic sentiment and there are massive layoffs, which can deeply hurt the economy.

References

1. Baek, ChaeWon, et al. "Employment 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 Employment." *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

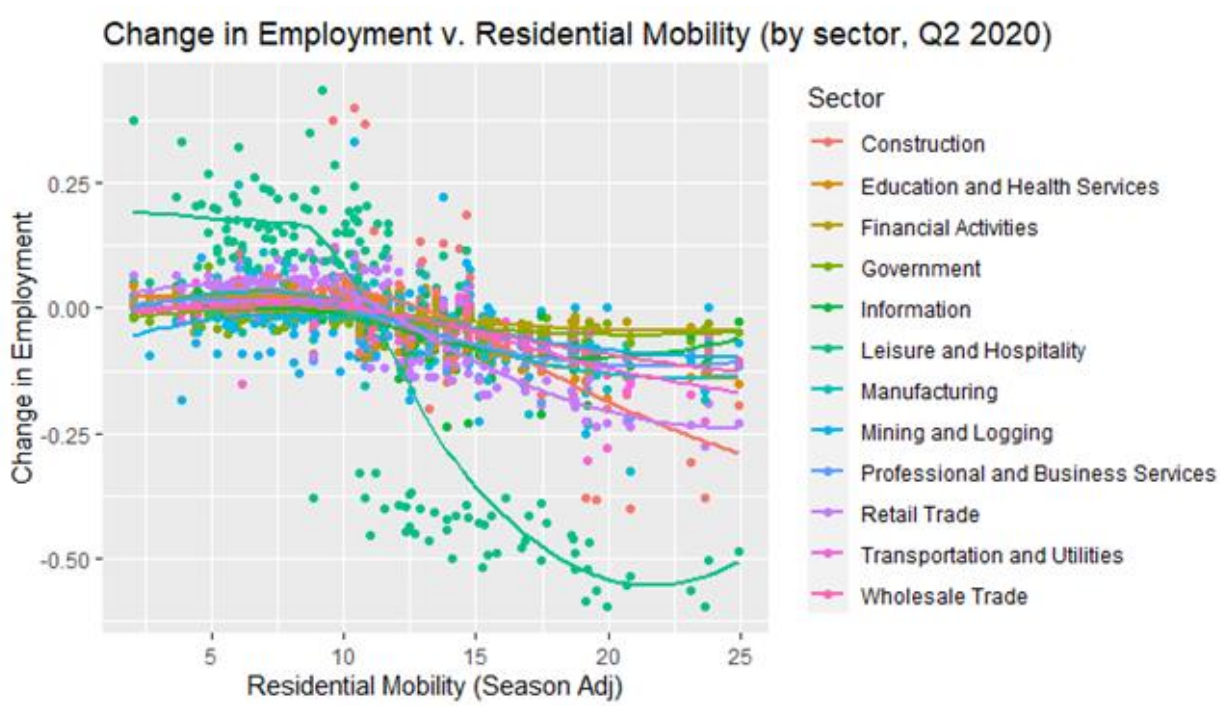

Figure 1: Plot of Mobility vs Change in Employment and Best Fit by Sector

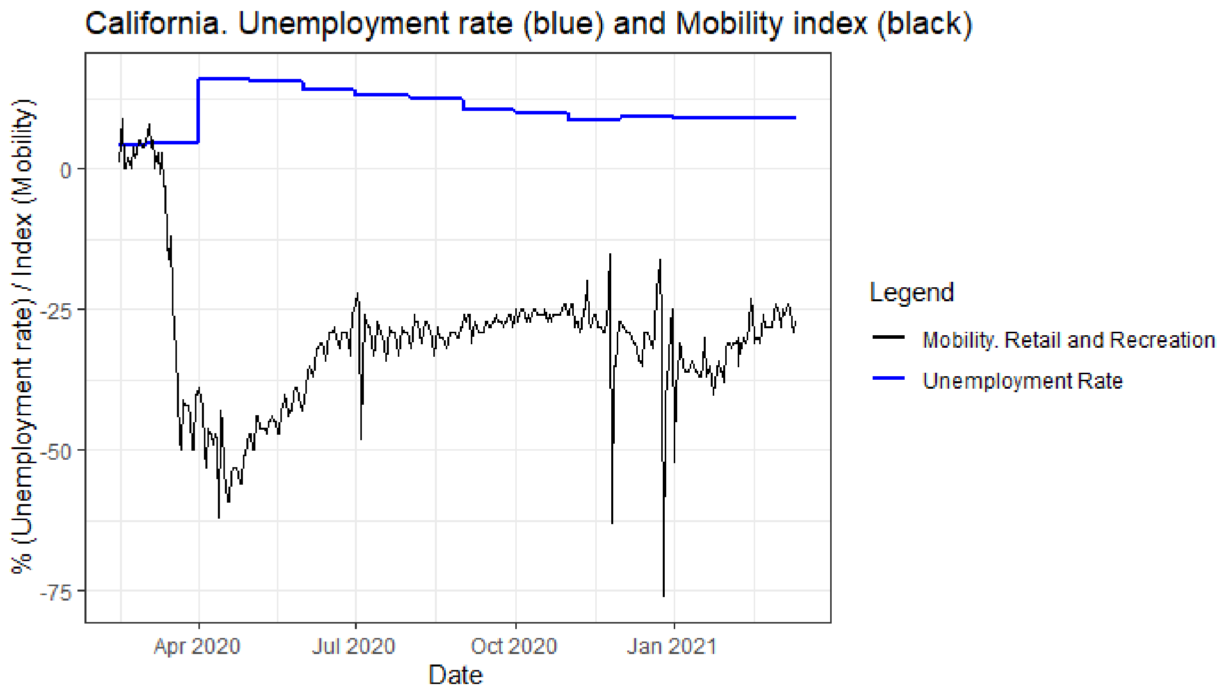

Figure 2: Plot of Employment Rate and Mobility Index over Time (California)

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)

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

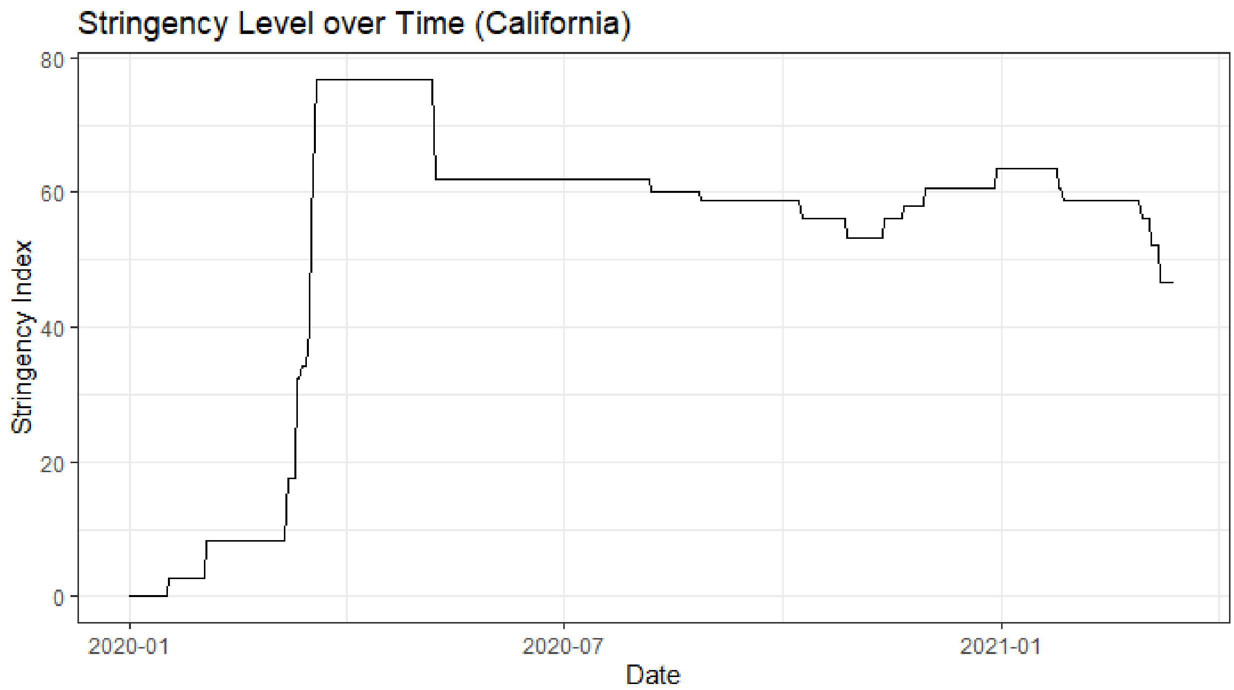

Figure 3: Plot of Stringency Index over Time (California)

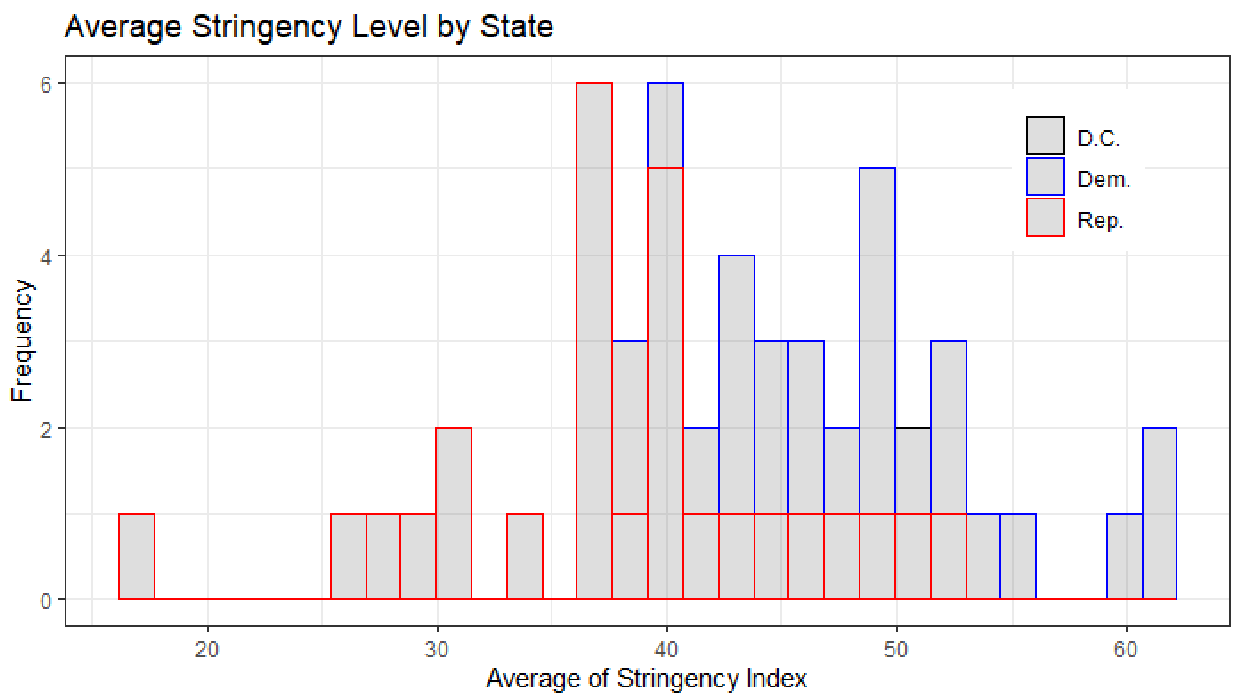

Figure 4: Plot of Stringency Index by State (Political Party)

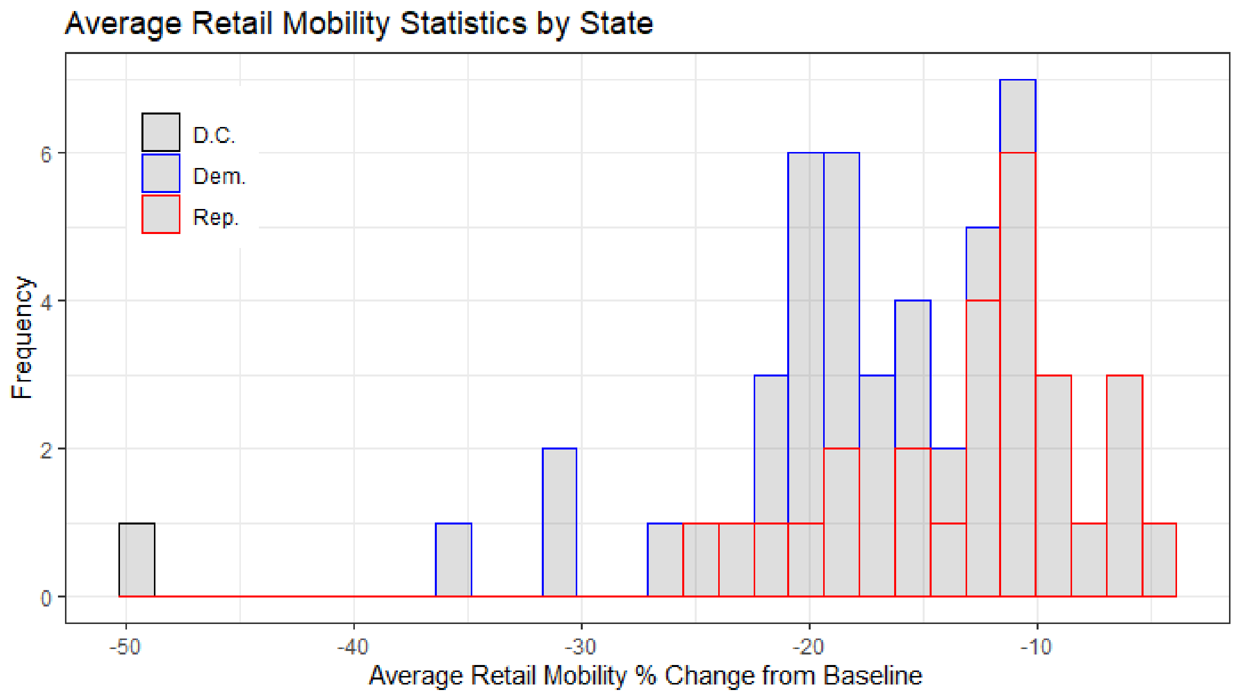

Figure 5: Plot of Retail Mobility by State (Political Party)

Dep. Variable:	change_in_emp	**R-squared:**	0.681
Model:	OLS	**Adj. R-squared:**	0.675
Method:	Least Squares	**F-statistic:**	99.83
Date:	Sun, 02 May 2021	**Prob (F-statistic):**	0.00
Time:	16:18:31	**Log-Likelihood:**	2510.8
No. Observations:	1812	**AIC:**	-4944.
Df Residuals:	1773	**BIC:**	-4729.
Df Model:	38		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.1286	0.023	5.605	0.000	0.084	0.174
C(Sector)[T.Education and Health Services]	0.0099	0.032	0.314	0.754	-0.052	0.072
C(Sector)[T.Financial Activities]	-0.0598	0.032	-1.890	0.059	-0.122	0.002
C(Sector)[T.Government]	-0.0674	0.032	-2.131	0.033	-0.129	-0.005
C(Sector)[T.Information]	-0.0220	0.032	-0.693	0.488	-0.084	0.040
C(Sector)[T.Leisure and Hospitality]	-0.0597	0.035	-1.712	0.087	-0.128	0.009
C(Sector)[T.Manufacturing]	0.0134	0.032	0.425	0.671	-0.049	0.075
C(Sector)[T.Mining and Logging]	-0.0897	0.032	-2.814	0.005	-0.152	-0.027
C(Sector)[T.Professional and Business Services]	-0.0135	0.032	-0.426	0.670	-0.076	0.049
C(Sector)[T.Retail Trade]	0.0833	0.032	2.633	0.009	0.021	0.145
C(Sector)[T.Transportation and Utilities]	-0.0122	0.032	-0.384	0.701	-0.074	0.050
C(Sector)[T.Wholesale Trade]	-0.0404	0.032	-1.277	0.202	-0.102	0.022
Mob_res_SA_leisig	-0.0175	0.001	-12.772	0.000	-0.020	-0.015
Mob_res_SA_leisig:C(Sector)[T.Education and Health Services]	0.0057	0.002	3.037	0.002	0.002	0.009
Mob_res_SA_leisig:C(Sector)[T.Financial Activities]	0.0124	0.002	6.604	0.000	0.009	0.016
Mob_res_SA_leisig:C(Sector)[T.Government]	0.0124	0.002	6.597	0.000	0.009	0.016
Mob_res_SA_leisig:C(Sector)[T.Information]	0.0097	0.002	5.140	0.000	0.006	0.013
Mob_res_SA_leisig:C(Sector)[T.Leisure and Hospitality]	1.0265	0.026	40.151	0.000	0.976	1.077
Mob_res_SA_leisig:C(Sector)[T.Manufacturing]	0.0042	0.002	2.263	0.024	0.001	0.008
Mob_res_SA_leisig:C(Sector)[T.Mining and Logging]	0.0102	0.002	5.252	0.000	0.006	0.014
Mob_res_SA_leisig:C(Sector)[T.Professional and Business Services]	0.0069	0.002	3.691	0.000	0.003	0.011
Mob_res_SA_leisig:C(Sector)[T.Retail Trade]	-0.0018	0.002	-0.934	0.350	-0.005	0.002
Mob_res_SA_leisig:C(Sector)[T.Transportation and Utilities]	0.0061	0.002	3.257	0.001	0.002	0.010
Mob_res_SA_leisig:C(Sector)[T.Wholesale Trade]	0.0090	0.002	4.806	0.000	0.005	0.013
stringency_index	0.0008	0.000	1.717	0.086	-0.000	0.002
stringency_index:C(Sector)[T.Education and Health Services]	-0.0013	0.001	-1.968	0.049	-0.003	-4.3e-06
stringency_index:C(Sector)[T.Financial Activities]	-0.0012	0.001	-1.837	0.066	-0.002	8.11e-05
stringency_index:C(Sector)[T.Government]	-0.0012	0.001	-1.875	0.061	-0.003	5.64e-05
stringency_index:C(Sector)[T.Information]	-0.0017	0.001	-2.577	0.010	-0.003	-0.000

stringency_index:C(Sector)[T.Leisure and Hospitality]	-0.0019	0.001	-2.996	0.003	-0.003	-0.001
stringency_index:C(Sector)[T.Manufacturing]	-0.0011	0.001	-1.617	0.106	-0.002	0.000
stringency_index:C(Sector)[T.Mining and Logging]	-0.0006	0.001	-0.951	0.341	-0.002	0.001
stringency_index:C(Sector)[T.Professional and Business Services]	-0.0012	0.001	-1.789	0.074	-0.002	0.000
stringency_index:C(Sector)[T.Retail Trade]	-0.0011	0.001	-1.698	0.090	-0.002	0.000
stringency_index:C(Sector)[T.Transportation and Utilities]	-0.0010	0.001	-1.487	0.137	-0.002	0.000
stringency_index:C(Sector)[T.Wholesale Trade]	-0.0010	0.001	-1.591	0.112	-0.002	0.000
blue_state	0.0227	0.004	5.646	0.000	0.015	0.031
red_state	-0.0356	0.004	-9.410	0.000	-0.043	-0.028
tot_death	5.376e-06	6.7e-07	8.024	0.000	4.06e-06	6.69e-06

Table 2: Regression Results and Coefficients for Q2 2020 Data

Dep. Variable:	change_in_emp	**R-squared:**	0.145
Model:	OLS	**Adj. R-squared:**	0.139
Method:	Least Squares	**F-statistic:**	24.03
Date:	Sun, 02 May 2021	**Prob (F-statistic):**	5.27e-153
Time:	16:18:31	**Log-Likelihood:**	13808.
No. Observations:	5436	**AIC:**	-2.754e+04
Df Residuals:	5397	**BIC:**	-2.728e+04
Df Model:	38		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.0047	0.002	1.992	0.046	7.45e-05	0.009
C(Sector)[T.Education and Health Services]	1.184e-05	0.003	0.004	0.997	-0.006	0.006
C(Sector)[T.Financial Activities]	-0.0007	0.003	-0.211	0.833	-0.007	0.006
C(Sector)[T.Government]	-0.0009	0.003	-0.292	0.770	-0.007	0.005
C(Sector)[T.Information]	-0.0040	0.003	-1.231	0.218	-0.010	0.002
C(Sector)[T.Leisure and Hospitality]	0.0168	0.003	5.225	0.000	0.011	0.023
C(Sector)[T.Manufacturing]	-0.0010	0.003	-0.301	0.763	-0.007	0.005
C(Sector)[T.Mining and Logging]	-0.0076	0.003	-2.301	0.021	-0.014	-0.001
C(Sector)[T.Professional and Business Services]	0.0010	0.003	0.315	0.753	-0.005	0.007
C(Sector)[T.Retail Trade]	0.0004	0.003	0.127	0.899	-0.006	0.007
C(Sector)[T.Transportation and Utilities]	-0.0024	0.003	-0.738	0.460	-0.009	0.004
C(Sector)[T.Wholesale Trade]	-0.0022	0.003	-0.682	0.495	-0.009	0.004
Mob_res_SA	-0.0007	0.000	-2.863	0.004	-0.001	-0.000
Mob_res_SA:C(Sector)[T.Education and Health Services]	-0.0001	0.000	-0.366	0.714	-0.001	0.001
Mob_res_SA:C(Sector)[T.Financial Activities]	0.0004	0.000	1.182	0.237	-0.000	0.001
Mob_res_SA:C(Sector)[T.Government]	0.0001	0.000	0.346	0.730	-0.001	0.001
Mob_res_SA:C(Sector)[T.Information]	-0.0002	0.000	-0.510	0.610	-0.001	0.000
Mob_res_SA:C(Sector)[T.Leisure and Hospitality]	-0.0050	0.000	-14.512	0.000	-0.006	-0.004
Mob_res_SA:C(Sector)[T.Manufacturing]	0.0002	0.000	0.650	0.516	-0.000	0.001
Mob_res_SA:C(Sector)[T.Mining and Logging]	0.0008	0.000	2.282	0.023	0.000	0.002
Mob_res_SA:C(Sector)[T.Professional and Business Services]	-5.939e-05	0.000	-0.173	0.863	-0.001	0.001
Mob_res_SA:C(Sector)[T.Retail Trade]	-0.0003	0.000	-0.855	0.393	-0.001	0.000
Mob_res_SA:C(Sector)[T.Transportation and Utilities]	-0.0001	0.000	-0.295	0.768	-0.001	0.001
Mob_res_SA:C(Sector)[T.Wholesale Trade]	0.0004	0.000	1.172	0.241	-0.000	0.001
stringency_index	0.0001	6.56e-05	1.684	0.092	-1.82e-05	0.000
stringency_index:C(Sector)[T.Education and Health Services]	3.888e-07	9.02e-05	0.004	0.997	-0.000	0.000
stringency_index:C(Sector)[T.Financial Activities]	-0.0001	9.02e-05	-1.275	0.202	-0.000	6.18e-05
stringency_index:C(Sector)[T.Government]	-4.642e-05	9.02e-05	-0.514	0.607	-0.000	0.000
stringency_index:C(Sector)[T.Information]	6.733e-05	9.09e-05	0.741	0.459	-0.000	0.000
stringency_index:C(Sector)[T.Leisure and Hospitality]	0.0008	9.02e-05	9.118	0.000	0.001	0.001

stringency_index:C(Sector)[T.Manufacturing]	-5.807e-05	9.02e-05	-0.643	0.520	-0.000	0.000
stringency_index:C(Sector)[T.Mining and Logging]	-8.845e-05	9.31e-05	-0.951	0.342	-0.000	9.4e-05
stringency_index:C(Sector)[T.Professional and Business Services]	1.301e-05	9.02e-05	0.144	0.885	-0.000	0.000
stringency_index:C(Sector)[T.Retail Trade]	9.999e-05	9.02e-05	1.108	0.268	-7.69e-05	0.000
stringency_index:C(Sector)[T.Transportation and Utilities]	0.0002	9.02e-05	1.681	0.093	-2.53e-05	0.000
stringency_index:C(Sector)[T.Wholesale Trade]	-7.658e-05	9.02e-05	-0.849	0.396	-0.000	0.000
blue_state	0.0010	0.001	1.416	0.157	-0.000	0.002
red_state	-0.0021	0.001	-3.247	0.001	-0.003	-0.001
tot_death	1.854e-07	4.74e-08	3.915	0.000	9.25e-08	2.78e-07

Table 3: Regression Results and Coefficients for non-Q2 2020 Data

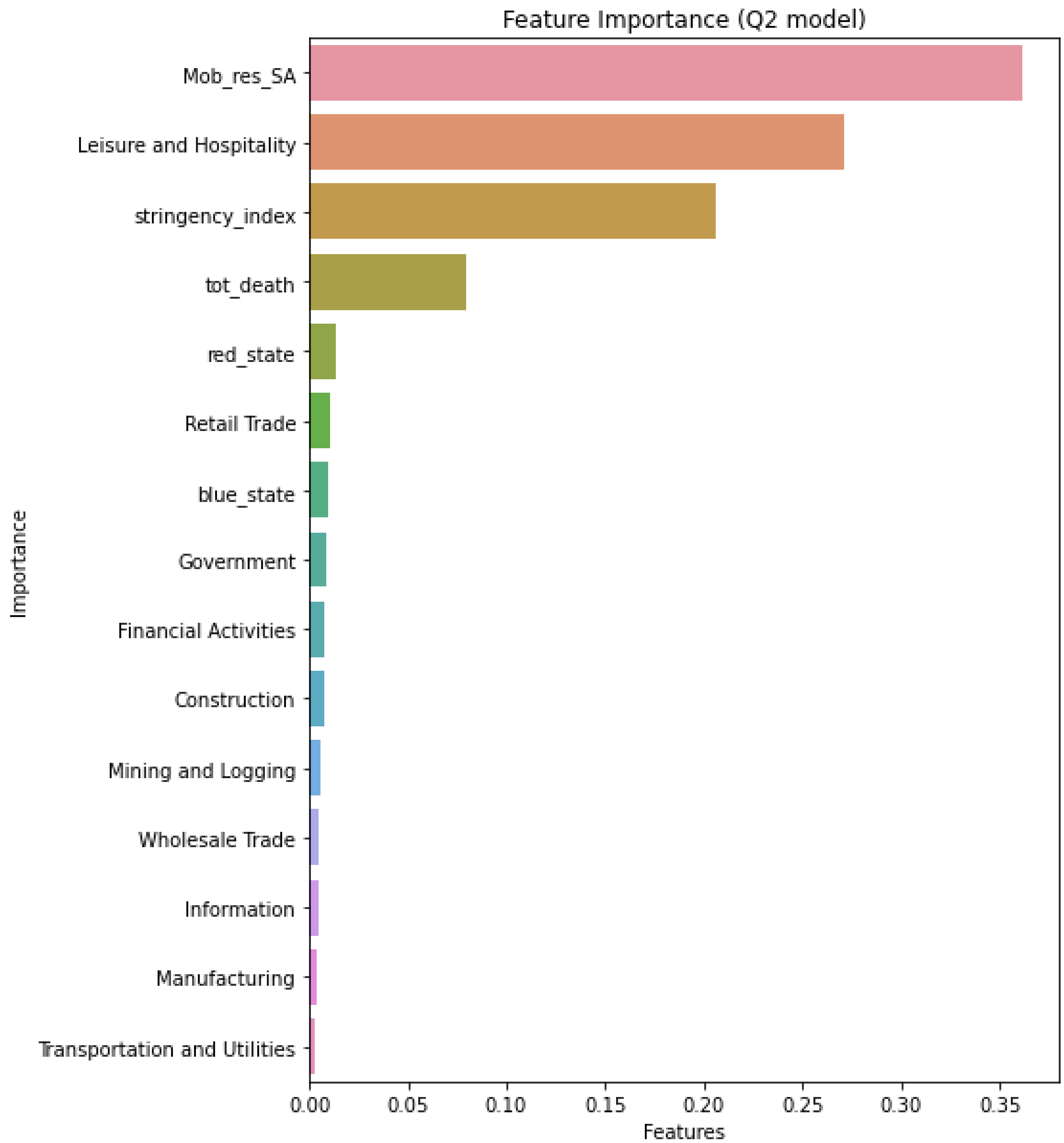

Figure 6: Most Important Features Regarding Change in Employment (Q2 2020)

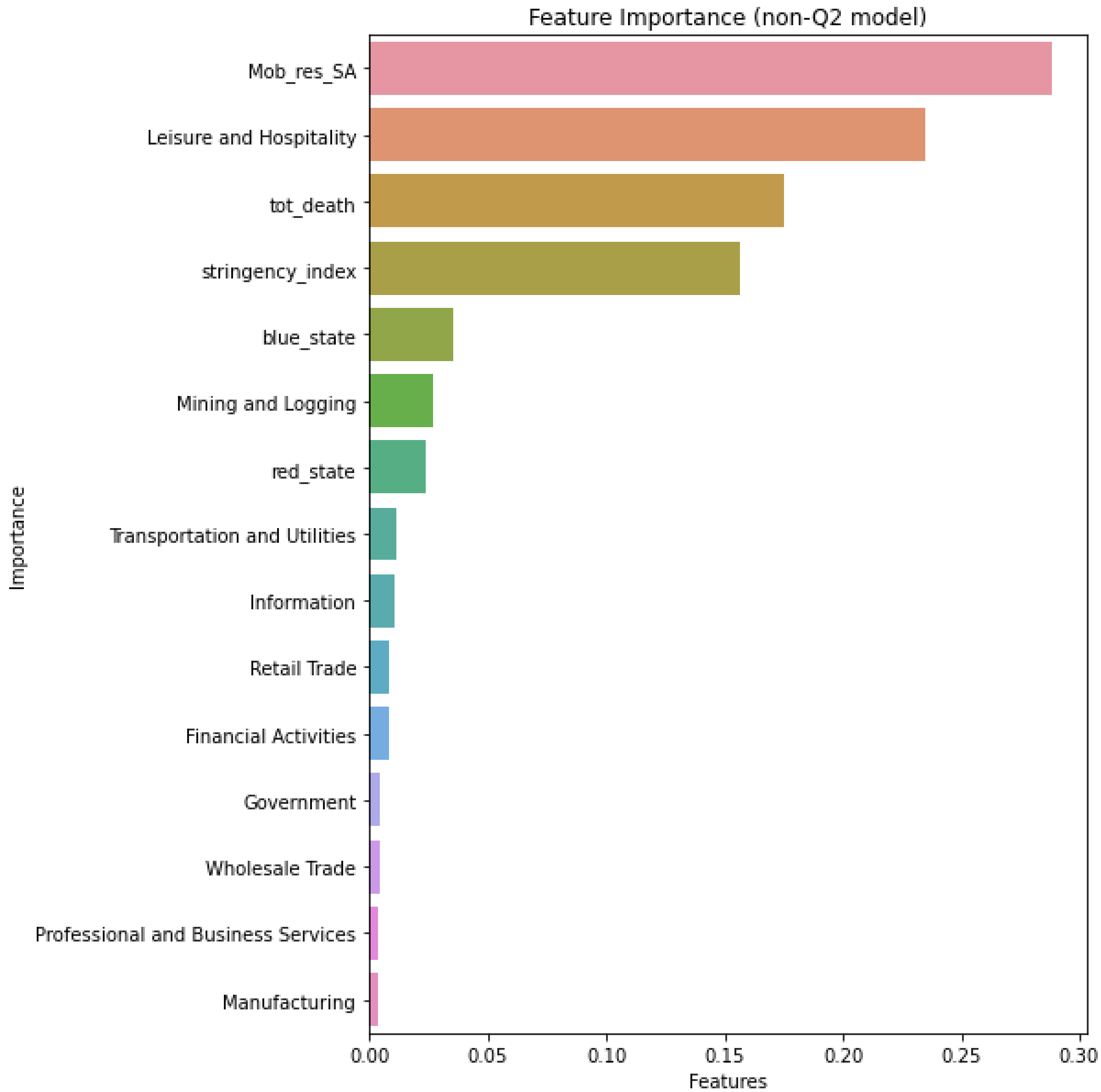

Figure 7: Most Important Features Regarding Change in Employment (non-Q2 2020)

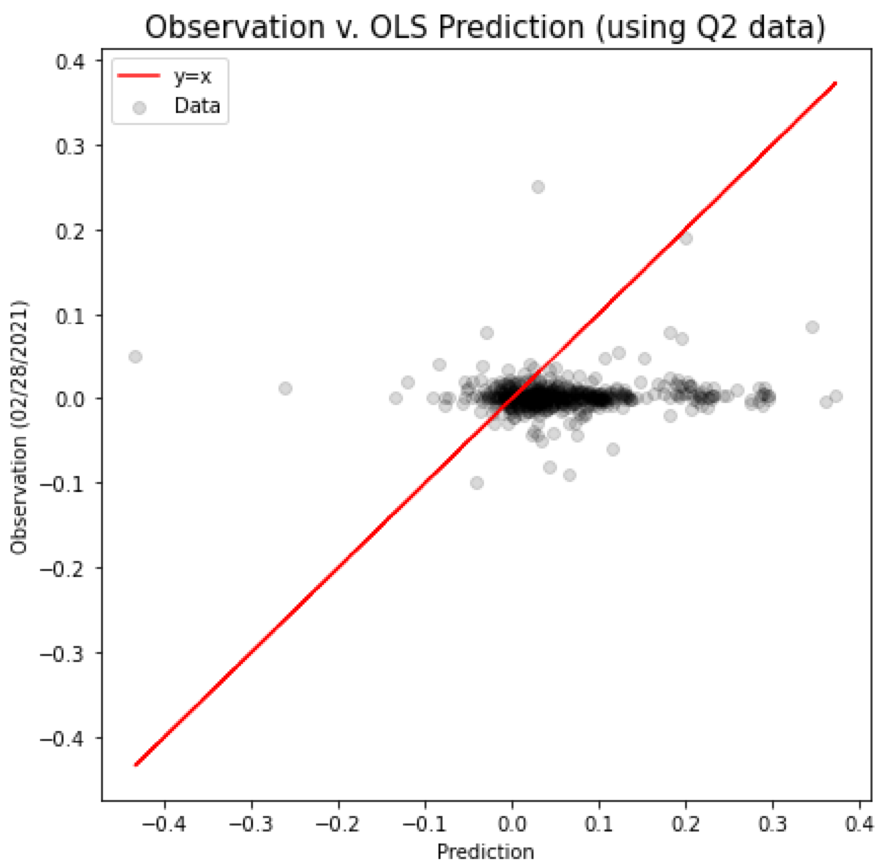

Figure 8: Plot of Actual versus Predicted Change in Employment (Q2 2020)

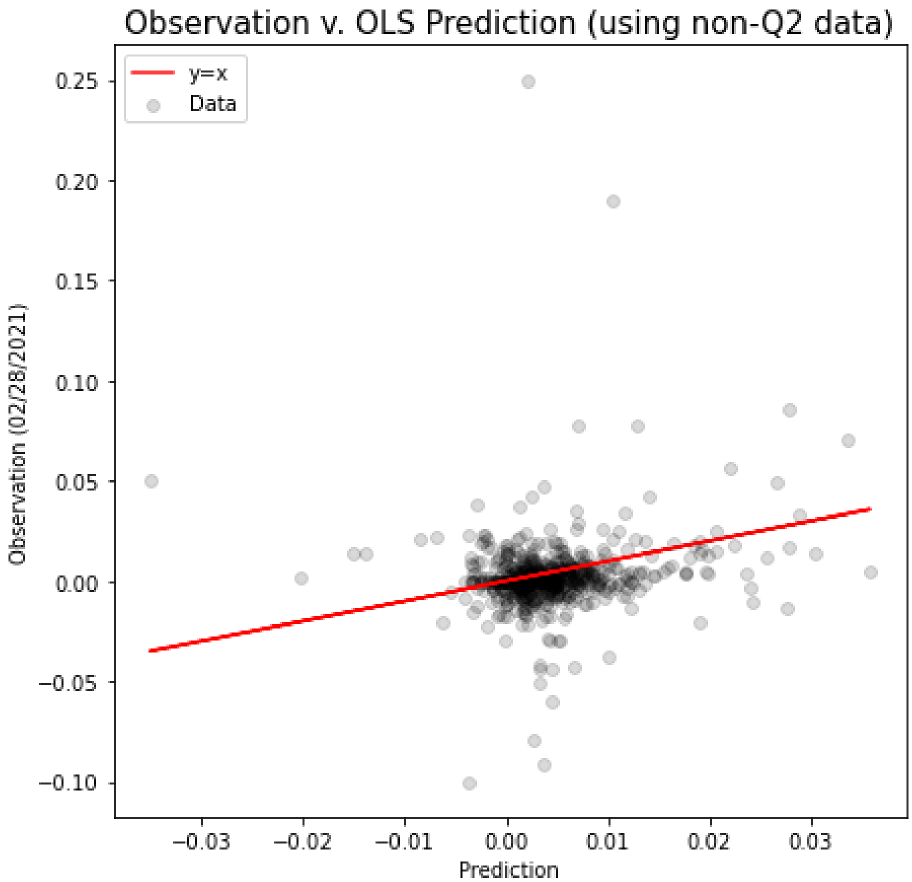

Figure 9: Plot of Actual versus Predicted Change in Employment (non-Q2 2020)