ECON 2509 Final Project Report

What factors contribute to the spread of Covid-19 in the US?

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Introduction

COVID-19 is a rapidly spreading global pandemic. As of 1st December 2020, there were about 64 millions confirmed cases and 1.5 millions deaths worldwide. The United States of America takes up over one fifth of total global confirmed cases, recorded to have 13 millions cases so far.[1] While there are no vaccines and effective antivirals available, the most effective available interventions are national lockdowns and quarantines for local and global control and mitigation of COVID-19.[2] Those interventions have changed our social lives in so many ways, as well as bringing consequences to our lives, and economy.[3]

Since Covid has such huge impact to our lives and economy, it is important to know factors actually contribute to the spread of it in US. This paper will be discussing a casual question - what factors contribute to the spread of Covid-19 in the US using multi-variable log-linear regression model.

To evaluate the topic, we compiled data from official credible sources, such as CDC, National Centers For Environmental Information, and United States Census Bureau to discuss how average temperature, uninsured rate, percentage of older population and if the state enforces any travel restrictions or not are the factors contributing to spread of it in US. The multi-variable log-linear regression model has concluded that four of the above listed factors are statistically significant regressor contributing to spread of covid in US.

Data Description

Table 1: A Glimpse of the dataset

state	month	cases	cases_log	avg_temp	precipitation	uninsured	older_pop	p_ratio	quarantine
Alabama	1	0	0.000000	49.6	7.40	9.7000	17.32634	0.55395	0
Alabama	2	0	0.000000	51.0	10.41	9.7000	17.32028	0.55395	0
Alabama	3	999	6.906755	63.4	6.17	9.7000	17.31422	0.55395	0
Alabama	4	6307	8.749415	61.9	7.09	16.5970	17.30816	0.55395	0
Alabama	5	10939	9.300090	68.8	3.64	13.1480	17.30211	0.55395	0
Alabama	6	19819	9.894396	76.9	5.15	13.1480	17.29605	0.55395	0
Alabama	7	49803	10.815831	80.8	5.29	13.1480	17.29000	0.55395	0
Alabama	8	38191	10.550355	80.2	5.83	13.1480	17.28395	0.55395	0
Alabama	9	28643	10.262664	74.3	4.99	13.1480	17.27791	0.55395	0
Alabama	10	37584	10.534334	66.8	4.79	13.1480	17.33241	0.55395	0
Alaska	1	0	0.000000	-6.2	1.89	15.6480	12.52498	0.71345	0
Alaska	2	0	0.000000	1.6	3.02	15.6480	12.52989	0.71345	0
Alaska	3	133	4.890349	12.0	2.28	15.6480	12.53480	0.71345	1
Alaska	4	222	5.402677	27.6	2.73	19.0970	12.53971	0.71345	1
Alaska	5	105	4.653960	43.4	1.49	19.0970	12.54462	0.71345	1

state	month	cases	cases_log	avg_temp	precipitation	uninsured	older_pop	p_ratio	quarantine
Alaska	6	480	6.173786	50.5	3.18	19.0970	12.54954	0.71345	1
Alaska	7	2050	7.625595	53.4	3.38	19.0970	12.55446	0.71345	1
Alaska	8	2273	7.728856	52.1	4.41	15.6480	12.55938	0.71345	1
Alaska	9	2561	7.848153	42.0	4.14	15.6480	12.56430	0.71345	1
Alaska	10	7450	8.915969	66.4	3.18	15.6480	12.52008	0.71345	1
Arizona	1	0	0.000000	43.7	0.45	13.0245	17.93581	0.92723	0
Arizona	2	0	0.000000	45.9	1.10	13.0245	17.89287	0.92723	0
Arizona	3	1288	7.160846	50.9	2.38	14.7480	17.85003	0.92723	0
Arizona	4	6359	8.757626	59.3	0.36	18.1970	17.80729	0.92723	1
Arizona	5	12288	9.416379	70.5	0.11	14.7480	17.76465	0.92723	1
Arizona	6	59279	10.990010	76.7	0.05	14.7480	17.72212	0.92723	0
Arizona	7	94795	11.459472	82.8	0.72	18.1970	17.67969	0.92723	0
Arizona	8	27825	10.233690	84.2	0.60	14.7480	17.63736	0.92723	0
Arizona	9	16672	9.721486	75.7	0.13	14.7480	17.59513	0.92723	0
Arizona	10	27439	10.219721	59.6	0.15	14.7480	17.97886	0.92723	0

Note: The above only shows the first 30 lines of the dataset. The full dataset is attached in page 19.

Table 2: Present variables, variable types and description

Variable	Variable Type	Variable Description
`state`	Categorical	The 49 states in the US
`month`	Discrete	Month of January to October in year 2020
`cases`	Discrete	Total number of Covid confirmed cases per month by state
`cases_log`	Continuous	Log of total number of Covid confirmed cases per month by state
`avg_temp`	Continuous	Average temperature per month by state
`precipitation`	Continuous	Total precipitation per month by state
`uninsured`	Continuous	Uninsured rate of the state in the respective month
`older_pop`	Continuous	Percentage of older population (65 years old +)
`quarantine`	Discrete	Binary indicator if the state enforces any travel restrictions

Note: Travel restrictions include self-quarantine for 14 days after arrival, completion of travel health form, and/or proof of negative covid test results from a CLIA certified laboratory before arrival.

Data Collection Description

Since different states in the US have different geographical and demographic characteristics and policies, our data is based off every state by month. The time period covered was from January to October of the year 2020. All the data sources and important assumptions of out data are as follow:

Table 3: Data sources

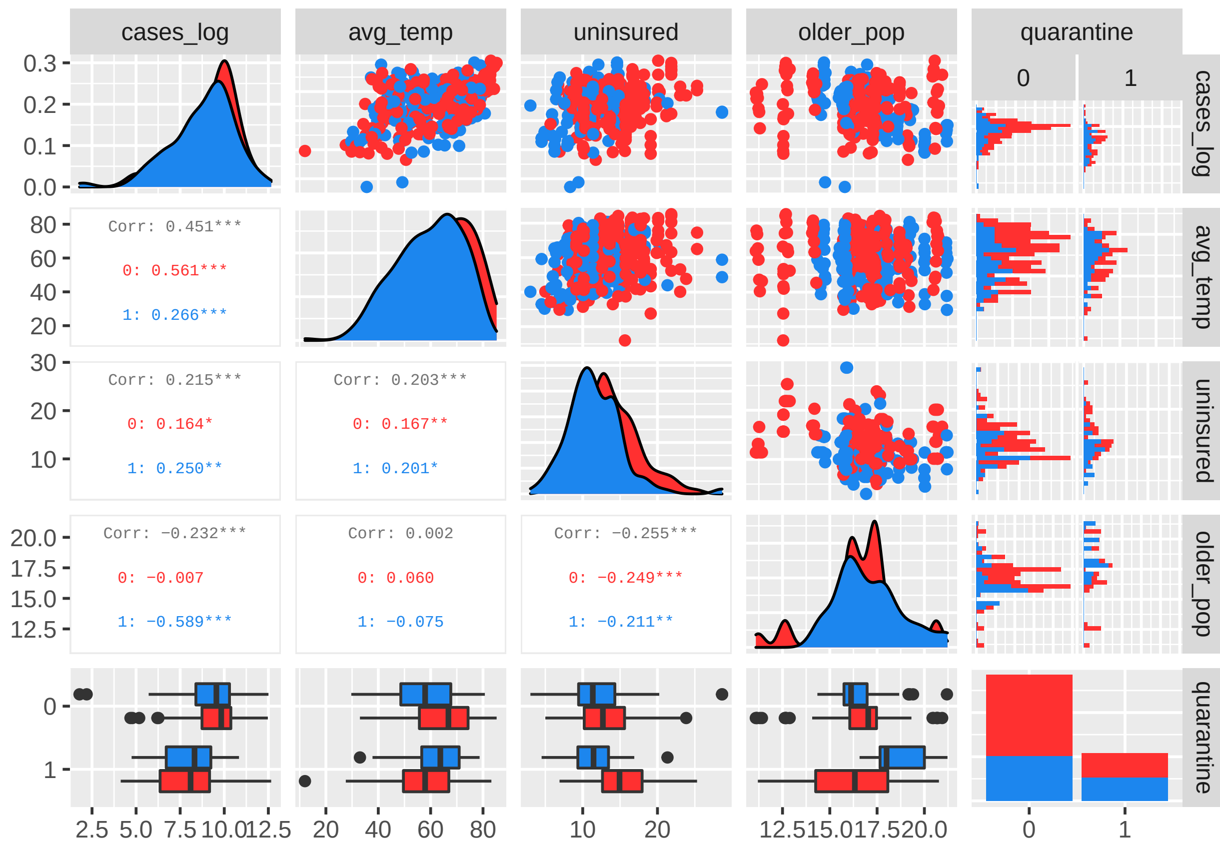
Variable	Sources
`cases`	Centers of Disease Control and Prevention
`avg_temp`	National Centers For Environmental Information
`precipitation`	National Centers For Environmental Information
`uninsured`	Urban Institute
`older_pop`	United States Census Bureau
`quarantine`	Centers of Disease Control and Prevention

Assumptions

1. The variable `cases` is computed by taking the natural log of the total number of Covid confirmed cases per month by state. The natural log of 0 is undefined. Therefore, it is assumed that ln(0) is 0, ie. the growth rate of covid is 0 when the month is recorded to have no new confirmed cases in that month.
2. The variable `older_pop` is computed by dividing the senior population and total population in different months of the state. United States Census Bureau has provided a projected annual growth rate for total population and senior population. Here it is assumed that the growth rate is constant over the 10 months period.

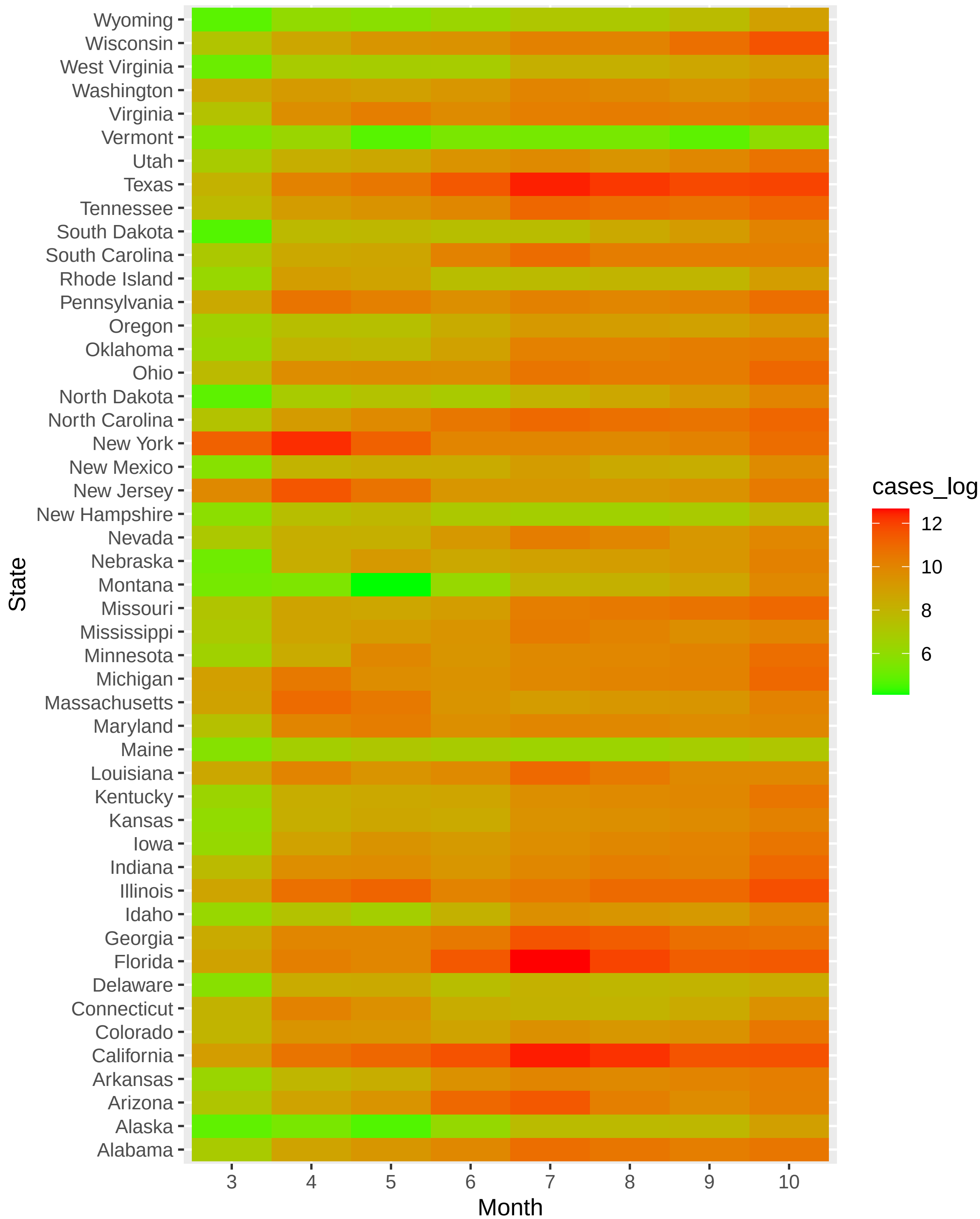
Basic Descriptive Statistics of the dataset

Figure 1: Distribution of variables of interest



From the diagonal graphs in figure 1, we can see that `avg_temp`, `uninsured` and `older_pop` seems to follow a normal distribution.

Figure 2: Heatmap of Covid growth rate of different states in 2020



state	month	cases	cases_log	avg_temp	precipitation	uninsured	older_pop	p_ratio	quarantine
Length:490	Min. : 1.0	Min. : 0.0	Min. : 0.000	Min. :-6.20	Min. : 0.040	Min. : 3.00	Min. :11.09	Min. :0.3211	0:382
Class :character	1st Qu.: 3.0	1st Qu.: 449.2	1st Qu.: 6.107	1st Qu.:43.48	1st Qu.: 1.510	1st Qu.: 9.43	1st Qu.:16.01	1st Qu.:0.6352	1:108
Mode :character	Median : 5.5	Median : 6271.0	Median : 8.744	Median :57.85	Median : 3.115	Median :11.91	Median :16.88	Median :0.9272	NA
NA	Mean : 5.5	Mean : 18383.9	Mean : 7.232	Mean :56.09	Mean : 3.285	Mean :12.21	Mean :16.86	Mean :0.9526	NA
NA	3rd Qu.: 8.0	3rd Qu.: 21792.5	3rd Qu.: 9.989	3rd Qu.:69.80	3rd Qu.: 4.590	3rd Qu.:14.60	3rd Qu.:17.69	3rd Qu.:1.2075	NA
NA	Max. :10.0	Max. :315249.0	Max. :12.661	Max. :85.20	Max. :10.510	Max. :28.64	Max. :21.22	Max. :1.9524	NA

Table 4: This is the table caption

Econometric Strategy

Model:

Since number of covid confirmed cases grew rapidly in 2020, therefore we are more interested in its growth rate in different months by state. Other than that, the scatter plots in the first row of figure 1 shows that `avg_temp`, `uninsured` and `older_pop` likely have a linear relationship with `cases`. Therefore, a multiple variable log-linear regression model is being used to evaluate the factors contributing to the spread of Covid in US. It is assumed that all observations are independent and identically distributed and the expected value of the error term given X is zero, so as to obtain unbiased, consistent and efficient estimates.

Hypotheses & Expectations:

H_0: Average temperature, state's uninsured rate, percentage of older population, and enforcement of travel restrictions have no relationship, ie. are not factors contributing to the spread of Covid-19 in the US.

H_1: Average temperature, state's insured rate, percentage of older population, and enforcement of travel restrictions have a relationship, ie. are factors contributing to the spread of Covid-19 in the US.

Expectations:

According to the scatter plots in the first row of figure 1, `avg_temp` and `uninsured` have a positive relationship with `cases`. It is expected that the higher the average temperature and uninsured rate will lead to a higher covid growth rate. However, the data of `older_pop` is a little dispersed. It is hard to tell from the scatter plot if percentage of older population will have a positive or negative with covid growth rate.

Mutlicollinearity, Heteroskoskasticity, Omitted variable biased and/or data limitations:

1. Mutlicollinearity & Heteroskoskasticity:

To avoid the problem of mutlicollinearity and heteroskoskasticity in our model, we computed VIF values of regression variables and checked the correlation between the variables, as well as performed some regression diagnostic plots, like Residual vs fitted and Scale-Location plot, to help checking for such issues in our model. None of the above issues were found after we performed the checkings.

2. Omitted variable:

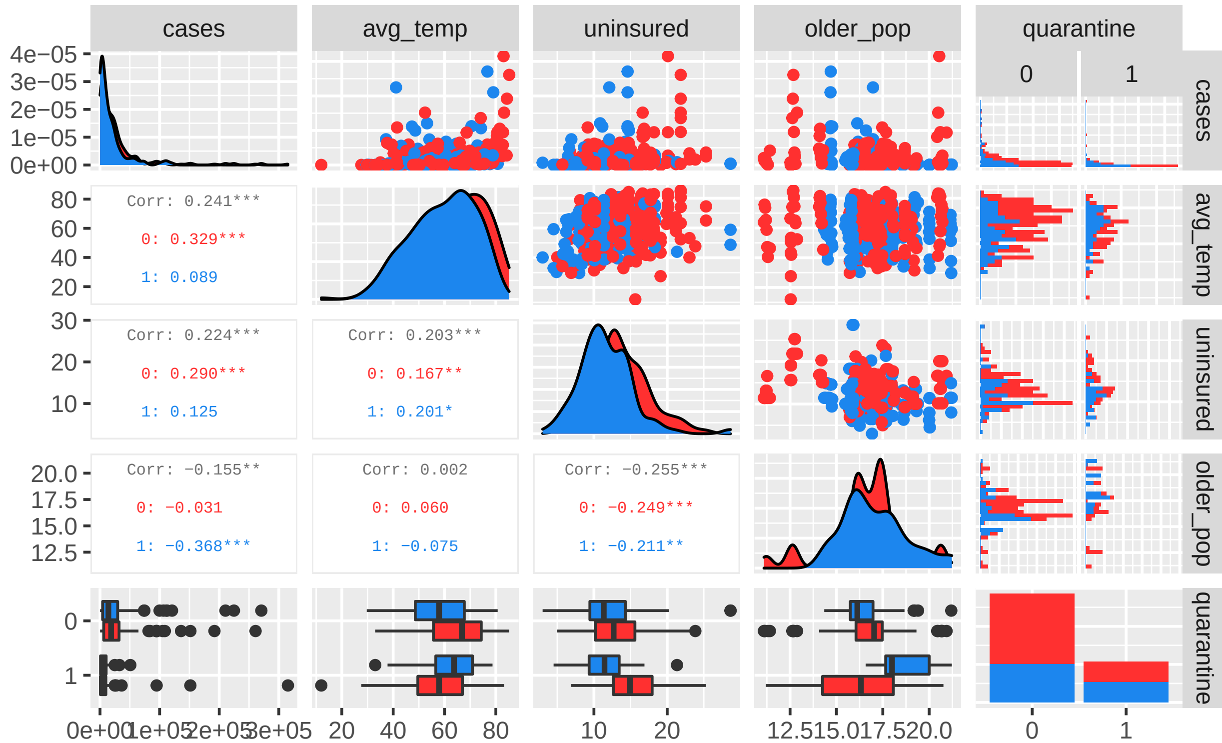
Excluding precipitation will cause omitted variable bias, because of the following:

1. Precipitation is correlated with the regressor `avg_temp` - as average temperatures at the Earth's surface rise, more evaporation occurs, which, in turn, increases overall precipitation. Therefore, a warming climate is expected to increase precipitation in many areas.
2. Precipitation is a determinant of the growth rate of Covid confirmed cases - precipitation boosts the 'stay-home' rules and and lower the opportunity of virus exposure.[4]

The omitted variable "precipitation" was being considered. It was being added in the multiple variable log-linear regression model as an additional regressor so as to overcome omitted variable biased.

Alternative model:

Figure 3: Distribution of variables of interest with cases as the independent variable



Other alternative model, like non-linear multi-variable polynomial regression model was being considered as well. From the scatter plots in the first row of figure 3, it shows that `avg_temp` and `uninsured` likely have an exponential relationship with `cases`. Therefore, even though the non-linear multi-variable polynomial regression model result has a high chance of being reasonable, it is not ideal to have big standard errors to construct confidence intervals. As a result, multi-variable log-linear regression model was eventually chosen as the optimum model to evaluate the topic.

Results:

Multi-variable Log-linear regression model results:

```
Call:
lm(formula = df$cases_log ~ (df$avg_temp + df$precipitation +
    df$uninsured + df$older_pop + df$quarantine))

Residuals:
    Min      1Q  Median      3Q     Max
-6.4681 -0.7882  0.0321  0.8154  4.0624

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)       7.804442   0.787996   9.904  < 2e-16 ***
df$avg_temp       0.049761   0.005536   8.989  < 2e-16 ***
df$precipitation  0.058957   0.036853   1.600  0.11046
df$uninsured      0.053030   0.019214   2.760  0.00605 **
```

```
df$older_pop     -0.142323   0.039620  -3.592  0.00037 ***
df$quarantine1   -1.264832   0.161474  -7.833 4.61e-14 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.384 on 388 degrees of freedom
Multiple R-squared:  0.3688,    Adjusted R-squared:  0.3606
F-statistic: 45.34 on 5 and 388 DF,  p-value: < 2.2e-16
```

Interpret all the statistically significant predictors:

From the multi-variable log-linear regression model, we can see that the statistically significant predictors of covid growth rate are average temperature, uninsured rate, older population and if the state enforces travel restrictions. When the respective predictors are statistically significant, it means that we can reject the null hypothesis of "the variables and covid growth rate do not have relationship between one another" at a decent level of confidence. Thus, we have evidence to believe that the estimates are good.

Interpret each coefficient's p-value:

The p-values of those statistically significant predictors have numerical values close to 0, ie. very small. It indicates the probability of getting the a value as extreme as the respective t value is very small. Say we have an alpha value of 0.05, we reject the null hypothesis because their respective p-values are smaller than 0.05. It means that with 95% confidence, we reject the null hypothesis and there are evidence to support the alternative hypothesis.

Interpret the adjusted R-Square:

Since adjusted R square is 0.3606, it means that 36.06% of the actual variation is explained by the model.

Interpret of coefficients:

1. For every fahrenheit increase in average temperature, covid growth rate increases by 4.98%.

   Meanwhile different academic papers have big debates over the effect of temperature to the spread of covid. Some used the US covid date from January to April of 2020 and concluded that majority of the cases were found to be reported in states experiencing cold temperature between 4 and 11 °C.[5] Some conducted experiments in laboratory environment, which temperature was the only variable contribute to the growth of coronavirus in the experiment. The research results have found out coronavirus growth rate peaks in colder conditions.[6]

   However, the real life data collected were not conducted in laboratory environment. There are human factors adding to the temperature condition. For example, weather influences the environment in which the coronavirus must survive before infecting a new host. But it also influences human behavior and mobility, which moves the virus from one host to another. It is believed that higher temperature flavors outdoor human movements and further foster the spread of coronavirus. Therefore, having a positive coefficient for B1 is totally reasonable.

2. For every % increase in uninsured rate, covid growth rate increases by 5.30%.

   Medical expenses with insurance are costly in US. It is even more expensive without insurance.[7] For many Americans, a trip to the doctor hinges on whether they can afford to go, rather than if it's a medical necessity. Over the past year, 22% of Americans say they have avoided some of the medical expenses by skipping doctor visits, medications, vaccinations, annual exams because of the expense.[8] It is believed that people having symptoms of Covid concern it would be too expensive to get treated, and thus delay seeking medical attention. This ultimately increases the chances of moving the virus from one host to another.[9]

3. For every % increase in older population, covid growth rate decreases by 14.23%

   Academic papers have big debates over whether older population has a higher chance of getting covid or not, and thus ultimately contribute to the covid growth rate if the state has a high percentage of senior population. Some stated from the physical point of view that older people don't have as strong an immune system so they are more vulnerable to infectious disease. They're also more likely to have conditions such as heart disease, lung disease, diabetes or kidney disease, which weaken their body's ability to fight infectious disease.[10]Some acknowledged the physical reason, but stated from the social point of view that a lot of the seniors have isolation or mobility challenges. So because they're isolated, they can't get around for basic necessities or even have social gatherings.[11]

   According to more academic papers that were released lately, covid impacts all ages, including kids. It seems that age is no longer causing a debate towards covid growth rate. However, there are human factors adding to the age condition. As mentioned above, many seniors have isolation or mobility challenges. Unlike the young and mid age that are active to go to school and/work, seniors compared to have lower chance to be in contact with others that they have little chance in getting infected, which contribute to a negative coefficient in older_pop.

4. When state enforces travel restrictions in the particular month, covid growth rate decreases by 126.48%.

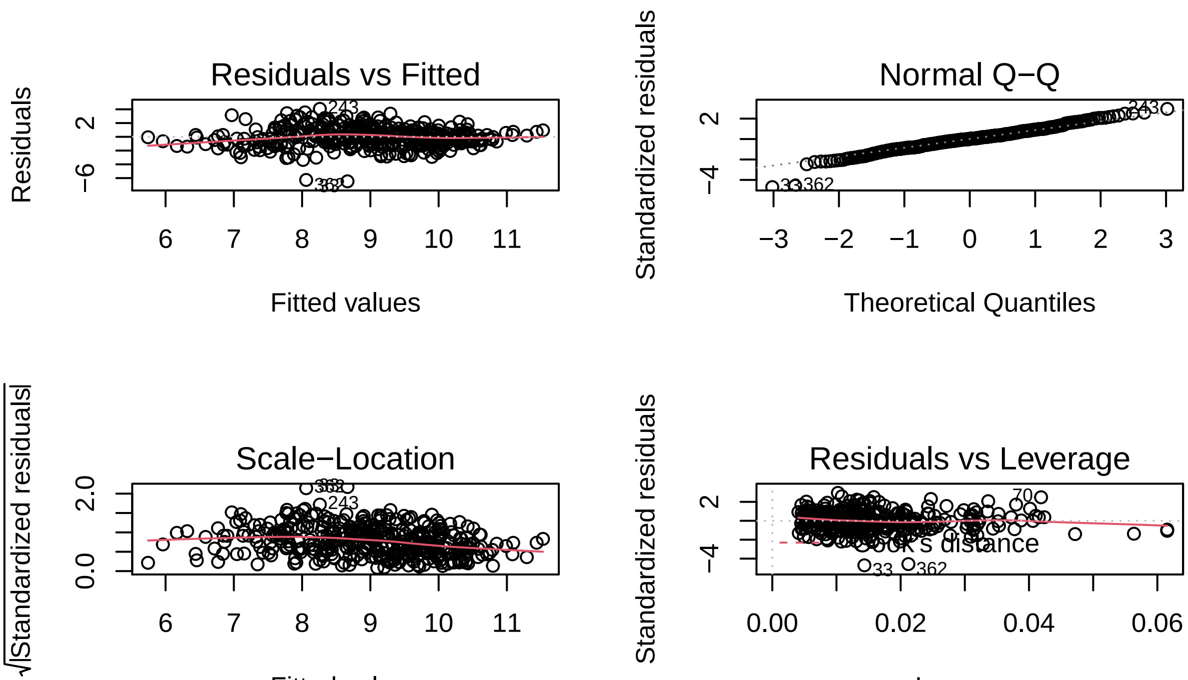
   Last but not least, acedemic papers have diverse conclusions in whether enforcement of travel restrictions is effective for reducing the spread of COVID-19. Some academic papers suggested that although President Trump signed an order banning most legal immigration from abroad in April. However, the bans didn't and couldn't stop all travel by U.S. citizens and legal permanent residents and thus travel restrictions fail to stop the spread of covid.[12] Some suggested that the enoforcement of travel restrictions unflavors travels to plan their trip with the fear of affecting travel experience.[13]

   The enforcement of travel restrictions and drastic local/national lockdown measures are believed to be the main reasons that decreases public appetite for travelling. The finanical and time cost for 14 days of self-quarantine after arrivial is unflavoring human activities and thus contribute to a negative coefficient in quarantine.

Check for Mutlicollinearity & Heteroskoskasticity

```
df$avg_temp df$precipitation     df$uninsured     df$older_pop     df$quarantine
   1.116293         1.111204         1.142464         1.177669          1.066879
```

Figure 4: Multi-variable Log-linear regression model plots



Observations:

1. From the Residuals vs fitted plot shows a horizontal straight line, which indicates that heteroscedasticity is not an issue.
2. Normal Q-Q plot shows a straight line, which indicates that the data follows normal distribution.
3. The Scale-Location plot helps spotting if the residuals are spread equally along the predictor range. In echo with the Residuals vs fitted plot, it shows a horizontal straight line, which indicates that heteroscedasticity is not an issue.
4. Correlation and VIF of all dependenet variables have values between 0.1 to 0.3 and 1 to 1.2 respectively, which indicates that multicollinearity unlikely exists in the model.

Note:

Variance inflation factor (VIF) is a measure of the amount of multicollinearity in a set of multiple regression variables. A value higher than 10 indicates high correlation.

Confidence Intervals:

```
                        2.5 %      97.5 %
(Intercept)        6.25516523  9.35371920
df$avg_temp        0.03887624  0.06064479
df$precipitation -0.01349987  0.13141368
df$uninsured       0.01525372  0.09080648
df$older_pop      -0.22022025 -0.06442522
df$quarantine1    -1.58230641 -0.94735835
```

The confidence intervals for all coefficients at 95% significance level are computed above. It means that we are 95% confident that the respective confidence interval contains the true mean of the population.

Comparision with various models

1. Mutli-variable non-linear polynomial regression model

```
Call:
lm(formula = cases ~ exp(avg_temp) + uninsured + older_pop +
    quarantine, data = df)

Residuals:
   Min     1Q Median     3Q    Max
-93151 -15810  -6396   4085 268447

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)    1.986e+04  1.764e+04   1.126  0.26101
exp(avg_temp)  2.539e-32  2.864e-33   8.865  < 2e-16 ***
uninsured      1.486e+03  4.480e+02   3.316  0.00100 ***
older_pop     -8.277e+02  9.124e+02  -0.907  0.36485
quarantine1   -1.416e+04  3.784e+03  -3.743  0.00021 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 32690 on 389 degrees of freedom
Multiple R-squared:  0.246, Adjusted R-squared:  0.2382
F-statistic: 31.73 on 4 and 389 DF,  p-value: < 2.2e-16
```

Other non linear model, like non-linear multi-variable polynomial regression model was being considered as alternative model. However, it is not ideal to have big standard errors to construct confidence intervals. As a result, multi-variable log-linear regression model was eventually chosen as the optimum model to evaluate the topic.

2. Subset one third of the 49 states in US

Further investigation was done to see if the multi-variable log-linear regression model provides the same statistically significant results. By using R to subset one third of the 49 states in US at random and run the same non-linear model, the results are as follow:

```
Call:
lm(formula = df_select$cases_log ~ (df_select$avg_temp + df_select$precipitation +
    df_select$uninsured + df_select$older_pop + df_select$quarantine))

Residuals:
     Min       1Q   Median       3Q      Max
-2.83406 -0.64285 -0.00791  0.69742  2.69872

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)              8.215920   1.268774   6.475 2.08e-09 ***
df_select$avg_temp       0.035140   0.008777   4.004 0.000107 ***
df_select$precipitation  0.044189   0.056558   0.781 0.436137
```

```
df_select$uninsured      0.080106   0.032291   2.481 0.014474 *
df_select$older_pop     -0.128596   0.063221  -2.034 0.044112 *
df_select$quarantine1   -0.912497   0.253354  -3.602 0.000458 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.162 on 122 degrees of freedom
Multiple R-squared:  0.3122,    Adjusted R-squared:  0.2841
F-statistic: 11.08 on 5 and 122 DF,  p-value: 8.234e-09
```

From the above, we can see that `avg_temp`, `uninsured`, `older_pop` and quarantine remain statistically significant in this subset model. However, the sample size shrunk to about 163 observations. This increases the margin of error, which, in return, increases the sensitivity of the regression model.

3. Subset the states according to political stance

(a) Result of Democrat States:

```
Call:
lm(formula = df_d$cases_log ~ (df_d$avg_temp + df_d$precipitation +
    df_d$uninsured + df_d$older_pop + df_d$quarantine))

Residuals:
    Min      1Q  Median      3Q     Max
-7.2651 -0.7159 -0.0036  0.7557  3.8469

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)        15.745483   1.633975   9.636  < 2e-16 ***
df_d$avg_temp       0.029664   0.009764   3.038  0.00282 **
df_d$precipitation  0.118309   0.065184   1.815  0.07155 .
df_d$uninsured      0.061914   0.032818   1.887  0.06118 .
df_d$older_pop     -0.566098   0.084414  -6.706 3.94e-10 ***
df_d$quarantine1   -0.249139   0.298589  -0.834  0.40541
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.41 on 148 degrees of freedom
Multiple R-squared:  0.4209,    Adjusted R-squared:  0.4013
F-statistic: 21.51 on 5 and 148 DF,  p-value: 3.843e-16
```

(b) Result of Republican States:

```
Call:
lm(formula = df_r$cases_log ~ (df_r$avg_temp + df_r$precipitation +
    df_r$uninsured + df_r$older_pop + df_r$quarantine))

Residuals:
    Min      1Q  Median      3Q     Max
-3.0482 -0.7626  0.0794  0.7212  3.6753
```

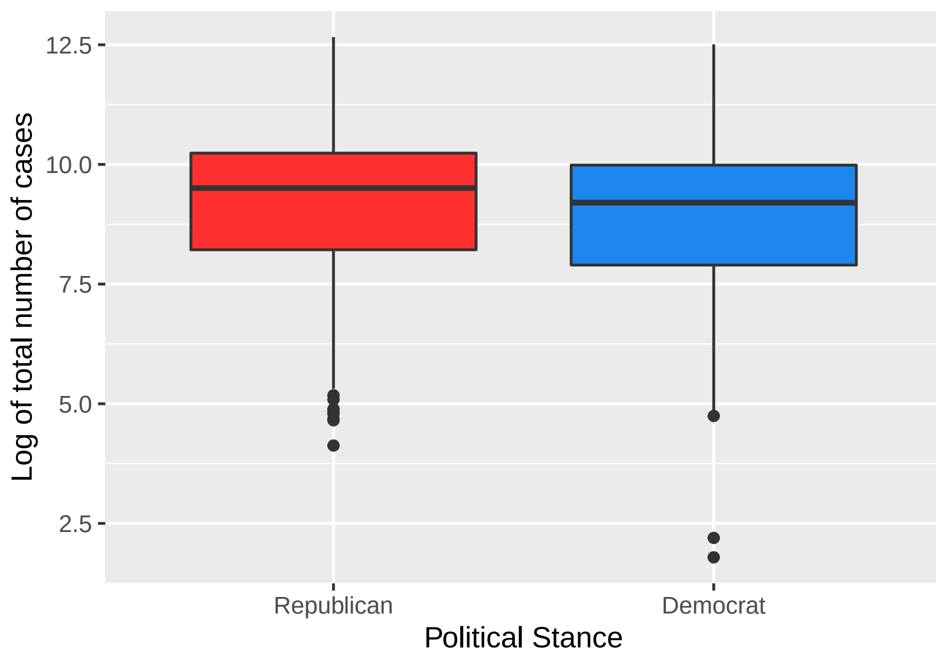
```
Coefficients:
                     Estimate Std. Error t value Pr(>|t|)    
(Intercept)           5.40268    0.89771   6.018 6.75e-09 ***
df_r$avg_temp         0.05431    0.00651   8.343 6.29e-15 ***
df_r$precipitation    0.03932    0.04398   0.894   0.3722    
df_r$uninsured        0.06862    0.02427   2.827   0.0051 ** 
df_r$older_pop       -0.02743    0.04400  -0.623   0.5336    
df_r$quarantine1     -1.35430    0.20797  -6.512 4.48e-10 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.271 on 234 degrees of freedom
Multiple R-squared:  0.4273,    Adjusted R-squared:  0.415 
F-statistic: 34.91 on 5 and 234 DF,  p-value: < 2.2e-16
```

From the above results, we can see that the only variable that remains statistically significant for both Democrat and Republican states is `avg_temp`. The variable quarantine becomes only statistically significant in Republican states, but not in Democrat States. Meanwhile, `uninsured` and `older_pop` are only statistically significant in either Republican or Democrat states.

Here are some graphs showing the comparison between the two groups below.

Figure 5: Boxplot of log of total number of cases by political stance



The boxplot in figure 5 shows the distribution of covid growth rate by political stance. Despite of the fact that the boxplot does not show big difference between the group, the scale of the y-axis, ie. covid growth rate was taking by the natural log of number of new confirmed covid cases per month by state. The difference between the the length of boxplot was greatly reduced by the natural log, and thus, Republican states have higher covid growth rates than Democrat states.

The scatter plot in figure 6 shows covid growth rate with respect to average temperature by political stance. In general, average temperature increases with covid growth rate regardless of the state's political stance.

The bar chart in figure 7 shows that total number of `cases` by political stance and travel restrictions. In Republican states, the total number of `cases` are significantly fewer in months that travel restrictions were

Figure 6: Log cases verse average temperature by travel restrictions enforcement

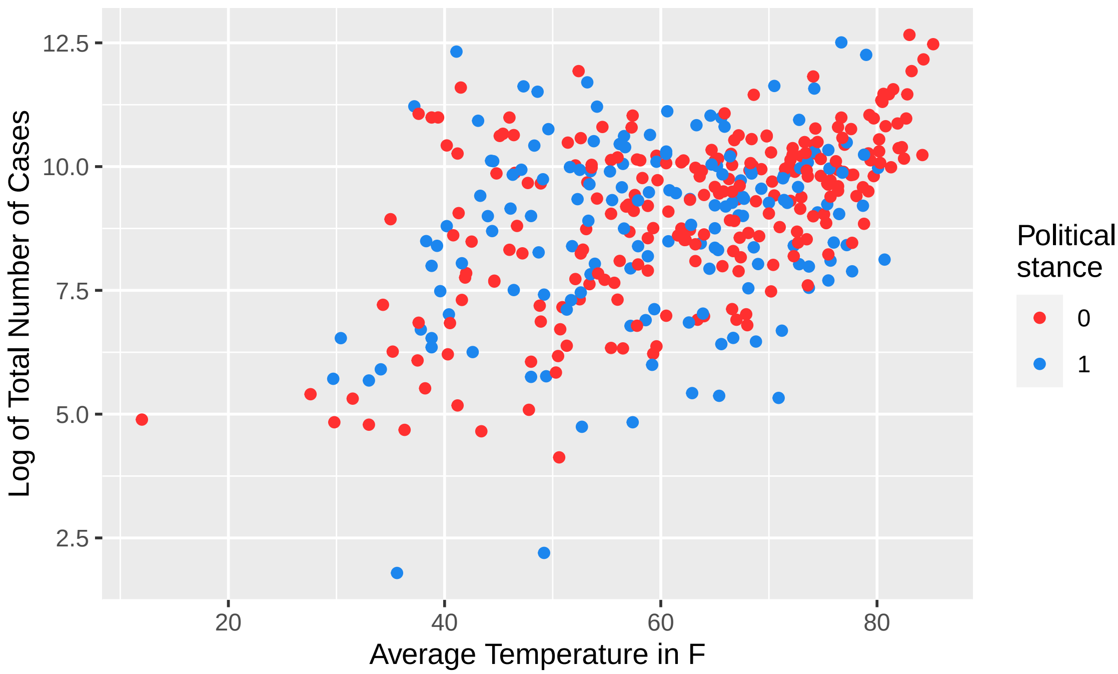
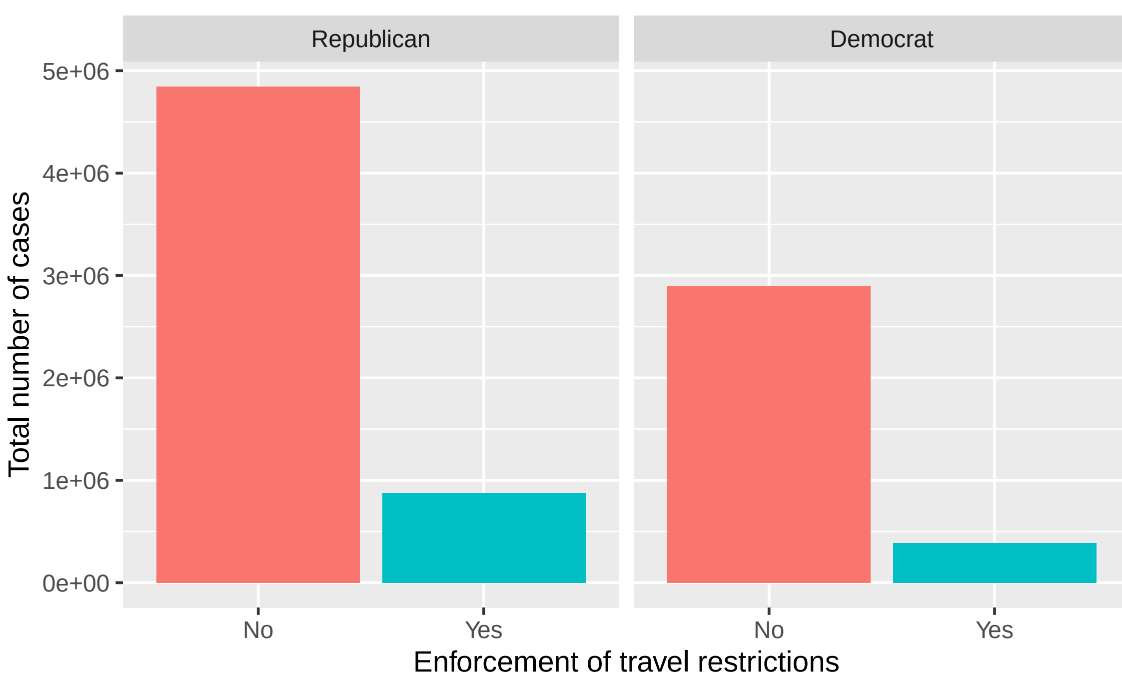


Figure 7: Total cases by travel restriction enforcement by political stance



enforced than were not enforcement; whereas in Democrat states, total number of `cases` are fairly similar in months that travel restrictions were enforced and not enforcement.

Logit Regression:

(a) Result of Democrat States:

```
Call:
glm(formula = cases_binary ~ avg_temp + precipitation + uninsured +
    older_pop + quarantine, family = "binomial", data = d_newdf)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.90646  -0.57589  -0.04409   0.53151   2.28763

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   14.59377    3.23483   4.511 6.44e-06 ***
avg_temp       0.09782    0.01954   5.006 5.56e-07 ***
precipitation  0.23805    0.12049   1.976   0.0482 *
uninsured      0.02997    0.05824   0.515   0.6068
older_pop     -1.24209    0.21027  -5.907 3.48e-09 ***
quarantine1   -0.12668    0.53570  -0.236   0.8131
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 262.87  on 189  degrees of freedom
Residual deviance: 144.40  on 184  degrees of freedom
AIC: 156.4

Number of Fisher Scoring iterations: 6
```

(b) Result of Republican States:

```
Call:
glm(formula = cases_binary ~ avg_temp + precipitation + uninsured +
    older_pop + quarantine, family = "binomial", data = r_newdf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.1292  -0.6076   0.2461   0.7086   2.2210

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -5.74301    1.60105  -3.587 0.000334 ***
avg_temp       0.10634    0.01277   8.327  < 2e-16 ***
precipitation -0.15308    0.07437  -2.058 0.039557 *
uninsured      0.07806    0.04498   1.735 0.082662 .
older_pop     -0.02893    0.08162  -0.354 0.723037
```

```
quarantine1   -1.78114    0.41663  -4.275 1.91e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 415.55  on 299  degrees of freedom
Residual deviance: 265.50  on 294  degrees of freedom
AIC: 277.5

Number of Fisher Scoring iterations: 5
```

Logit regression was performed to model the probability of covid growth rate is higher than its median of the respective political stance group - with 0 indicating that the covid growth rate of that month is not higher than the respective political stance group's median covid growth rate, and 1 indicating that the covid growth rate of that month is higher than the respective political stance group's median covid growth rate.

Similar results were obtained in both models considering statistically significant variables:

1. The independent variable `avg_temp` is statistically significant in both Republican and Democrat states. The positive coefficient of `avg_temp` indicates that average temperature and covid growth rate have a positive relationship, ie. the likelihood of rapid covid growth increases as average temperature increases. Also, the magnitude of the coefficient `avg_temp` in both Republican and Democrat states are very close.

2. The independent variable quarantine remains only statistically significant in Republican states, but not in Democrat States. The negative coefficient of quarantine indicates that the enforcement of travel restrictions and covid growth rate have a negative relationship, ie. the likelihood of rapid covid growth decreases when there is enforcement of travel restrictions. Also, there is a huge difference in the magnitude of the coefficient quarantine in Republican and Democrat states.

To further elaborate, the probability that covid growth rate is higher than its median of all Republican states with and without the enforcement of travel restrictions at average temperature of 70 Fahrenheit and precipitation of 5 inches are 0.303123 and 0.648233 respectively. Therefore,

1. The probability that covid growth rate is higher than its median of all Republican states increases by 0.34511028446 percentage points if travel restrictions were not enforced.
2. The probability that covid growth rate is higher than its median of all Republican states increases by 113% if travel restrictions were not enforced.

Limitations & Improvments

Limitations:

1. For OLS, it is assumed that all observations are independent and identically distributed. However, there are a lot of human factors that contribute to the growth rate of covid. For example, a person in the household caught covid and accidentally passed onto his/her family members or similar scenario in common work place, which, in turn causes bias estimators.

2. For OLS, it is also assumed that the expected value of the error term given X is zero. As mentioned above, there are a lot of human factors that contribute to the growth rate of covid. Those human factors are hard to measure and get data on, thus it is believed that the error term is not zero and will ultimately causes bias estimators.

3. The dataset only covers 10 months of covid data in 49 states of US. However, 95% of the states do not have covid confirmed cases in both January and February in 2020. Therefore, a relatively small data size of 400 was being used for the regression models.

4. While performing internal validity, the dataset was further split according to two categories, Democrat or Republican states. In echo with the previous limitation, the data size will become even smaller after categorizing for regression models. This enhances the linear model and logistic regression model to become sensitive to data changes.

5. In the regression models, it is assumed that uninsured rate contribute to covid growth rate. However, covid growth rate also contributes to uninsured rate as well. As number of covid cases increases, it is expected to have stricter local and national lockdowns. This leads to high unemployment rate due to getting laid off from various greatly impacted industries, like catering and tourism, and thus increases the percentage of people being uninsured after losing the health insurance granted through employment. The assumption causes simultaneous casualty bias.

Improvements:

1. The model can be improved by a larger dataset, which covers a longer period of time.

2. Implanting instrumental variable can eliminate the effect of simultaneous casualty bias as mentioned in limitation 5. One possible effective instrumental variable is the percentage of people getting emergency health insurance from state government for their lost of health insurance due to getting unemployed at covid times. However, this policy varies by state and the data is not available at the moment.

3. In some countries where they have very few covid cases, like Hong Kong and Taiwan, the governments have information about human factors that were previously discussed in the limitation. For example, family members of a covid carrier, attended the same 60-people-gathering as the covid carrier etc. The age, gender and the detail local/ international travel information of the covid carrier are also included. Those information about human factors are believed to play a big role in conducting a better model.

Conclusion

In gereral, average temperature, uninsured rate, percentage of older population and if the state enforces any travel restrictions or not are statistically significant factors contributing to spread of it in US. Those factors vary in being statistically significant in Democrat and Republican states. It is important that states with different political stance to learn from each other so as to stop the spread of covid.

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Table 5: A Glimpse of the dataset

state	month	cases	cases_log	avg_temp	precipitation	uninsured	older_popp_ratio		quarantine
Alabama	1	0	0.000000	49.6	7.40	9.7000	17.32634	0.55395	0
Alabama	2	0	0.000000	51.0	10.41	9.7000	17.32028	0.55395	0
Alabama	3	999	6.906755	63.4	6.17	9.7000	17.31422	0.55395	0
Alabama	4	6307	8.749415	61.9	7.09	16.5970	17.30816	0.55395	0
Alabama	5	10939	9.300090	68.8	3.64	13.1480	17.30211	0.55395	0
Alabama	6	19819	9.894396	76.9	5.15	13.1480	17.29605	0.55395	0
Alabama	7	49803	10.815831	80.8	5.29	13.1480	17.29000	0.55395	0
Alabama	8	38191	10.550355	80.2	5.83	13.1480	17.28395	0.55395	0
Alabama	9	28643	10.262664	74.3	4.99	13.1480	17.27791	0.55395	0
Alabama	10	37584	10.534334	66.8	4.79	13.1480	17.33241	0.55395	0
Alaska	1	0	0.000000	-6.2	1.89	15.6480	12.52498	0.71345	0
Alaska	2	0	0.000000	1.6	3.02	15.6480	12.52989	0.71345	0
Alaska	3	133	4.890349	12.0	2.28	15.6480	12.53480	0.71345	1
Alaska	4	222	5.402677	27.6	2.73	19.0970	12.53971	0.71345	1
Alaska	5	105	4.653960	43.4	1.49	19.0970	12.54462	0.71345	1
Alaska	6	480	6.173786	50.5	3.18	19.0970	12.54954	0.71345	1
Alaska	7	2050	7.625595	53.4	3.38	19.0970	12.55446	0.71345	1
Alaska	8	2273	7.728856	52.1	4.41	15.6480	12.55938	0.71345	1
Alaska	9	2561	7.848153	42.0	4.14	15.6480	12.56430	0.71345	1
Alaska	10	7450	8.915969	66.4	3.18	15.6480	12.52008	0.71345	1
Arizona	1	0	0.000000	43.7	0.45	13.0245	17.93581	0.92723	0
Arizona	2	0	0.000000	45.9	1.10	13.0245	17.89287	0.92723	0
Arizona	3	1288	7.160846	50.9	2.38	14.7480	17.85003	0.92723	0
Arizona	4	6359	8.757626	59.3	0.36	18.1970	17.80729	0.92723	1
Arizona	5	12288	9.416379	70.5	0.11	14.7480	17.76465	0.92723	1
Arizona	6	59279	10.990010	76.7	0.05	14.7480	17.72212	0.92723	0
Arizona	7	94795	11.459472	82.8	0.72	18.1970	17.67969	0.92723	0
Arizona	8	27825	10.233690	84.2	0.60	14.7480	17.63736	0.92723	0
Arizona	9	16672	9.721486	75.7	0.13	14.7480	17.59513	0.92723	0
Arizona	10	27439	10.219721	59.6	0.15	14.7480	17.97886	0.92723	0
Arkansas	1	0	0.000000	43.9	6.22	9.1000	17.34750	0.55611	0
Arkansas	2	0	0.000000	44.3	5.76	9.1000	17.33536	0.55611	0
Arkansas	3	560	6.327937	56.5	7.27	10.8245	17.32324	0.55611	0
Arkansas	4	2695	7.899153	58.8	6.04	15.9970	17.31112	0.55611	0
Arkansas	5	3998	8.293549	66.7	6.82	12.5480	17.29901	0.55611	1
Arkansas	6	13524	9.512221	76.4	4.72	12.5480	17.28691	0.55611	1
Arkansas	7	21734	9.986633	81.3	3.65	12.5480	17.27482	0.55611	0
Arkansas	8	18713	9.836974	77.8	6.73	12.5480	17.26273	0.55611	0
Arkansas	9	22473	10.020070	71.9	5.77	12.5480	17.25066	0.55611	0
Arkansas	10	28493	10.257414	66.5	4.59	12.5480	17.35964	0.55611	0
California	1	0	0.000000	45.3	2.06	9.4245	14.76367	1.95238	0
California	2	9	2.197225	49.2	0.21	9.4245	14.75187	1.95238	0
California	3	8119	9.001962	48.0	3.19	11.1480	14.74007	1.95238	0
California	4	40786	10.616094	56.6	1.98	14.5970	14.72829	1.95238	0
California	5	61666	11.029488	64.6	1.20	14.5970	14.71652	1.95238	0
California	6	112334	11.629232	70.5	0.15	14.5970	14.70475	1.95238	0
California	7	270671	12.508659	76.7	0.05	14.5970	14.69300	1.95238	0
California	8	210497	12.257227	79.0	0.09	14.5970	14.68125	1.95238	0
California	9	106540	11.576276	74.2	0.04	14.5970	14.66952	1.95238	0
California	10	111380	11.620703	47.3	0.05	11.1480	14.77548	1.95238	0

state	month	cases	cases_log	avg_temp	precipitation	uninsured	older_pop	p_ratio	quarantine
Colorado	1	0	0.000000	27.4	0.72	8.0000	14.59639	1.11316	0
Colorado	2	0	0.000000	26.4	1.09	8.0000	14.56447	1.11316	0
Colorado	3	2966	7.994969	38.8	1.36	11.4480	14.53262	1.11316	0
Colorado	4	12216	9.410502	43.3	0.80	14.8970	14.50084	1.11316	0
Colorado	5	11196	9.323312	55.5	1.08	14.8970	14.46913	1.11316	0
Colorado	6	6337	8.754161	65.0	1.13	14.8970	14.43749	1.11316	0
Colorado	7	14094	9.553505	69.3	1.84	11.4480	14.40591	1.11316	0
Colorado	8	10615	9.270023	70.0	0.80	11.4480	14.37441	1.11316	0
Colorado	9	13112	9.481283	58.9	0.99	11.4480	14.34298	1.11316	0
Colorado	10	36814	10.513633	53.8	0.57	11.4480	14.62838	1.11316	0
Connecticut	1	0	0.000000	33.2	2.05	7.6245	17.68110	1.33496	0
Connecticut	2	0	0.000000	34.0	3.25	7.6245	17.68508	1.33496	0
Connecticut	3	3128	8.048149	41.6	3.86	5.9000	17.68906	1.33496	0
Connecticut	4	24572	10.109363	44.5	5.19	9.3480	17.69304	1.33496	0
Connecticut	5	14501	9.581973	56.4	2.69	9.3480	17.69702	1.33496	0
Connecticut	6	4313	8.369389	68.6	2.47	12.7970	17.70100	1.33496	1
Connecticut	7	3296	8.100465	75.7	3.06	12.7970	17.70498	1.33496	1
Connecticut	8	3069	8.029107	72.8	2.43	9.3480	17.70897	1.33496	1
Connecticut	9	4671	8.449129	63.7	2.31	9.3480	17.71295	1.33496	1
Connecticut	10	13657	9.522008	60.8	4.97	9.3480	17.67712	1.33496	1
Delaware	1	0	0.000000	40.1	3.17	8.3245	19.37366	1.27338	0
Delaware	2	0	0.000000	41.8	3.30	8.3245	19.34738	1.27338	0
Delaware	3	319	5.765191	49.4	3.66	8.3245	19.32114	1.27338	1
Delaware	4	4415	8.392763	51.8	3.97	13.4970	19.29493	1.27338	1
Delaware	5	4872	8.491260	60.7	2.65	13.4970	19.26875	1.27338	1
Delaware	6	1904	7.551712	73.7	2.47	13.4970	19.24262	1.27338	1
Delaware	7	3367	8.121777	80.7	6.26	13.4970	19.21651	1.27338	0
Delaware	8	2658	7.885329	77.7	9.07	10.0480	19.19045	1.27338	0
Delaware	9	3078	8.032035	69.0	4.51	10.0480	19.16442	1.27338	0
Delaware	10	4513	8.414717	77.2	5.16	10.0480	19.39998	1.27338	0
Florida	1	0	0.000000	61.6	1.54	13.2000	20.88281	0.97531	0
Florida	2	0	0.000000	63.5	3.44	13.2000	20.82623	0.97531	0
Florida	3	6490	8.778018	71.0	0.54	14.9245	20.76981	0.97531	1
Florida	4	27200	10.210972	73.0	4.30	20.0970	20.71354	0.97531	1
Florida	5	21074	9.955795	75.7	5.05	20.0970	20.65742	0.97531	1
Florida	6	95017	11.461811	81.1	7.34	20.0970	20.60145	0.97531	1
Florida	7	315249	12.661118	83.0	8.18	20.0970	20.54563	0.97531	1
Florida	8	151599	11.928994	83.2	7.93	16.6480	20.48997	0.97531	1
Florida	9	81422	11.307401	80.5	9.02	16.6480	20.43446	0.97531	0
Florida	10	93946	11.450475	68.6	4.36	16.6480	20.93954	0.97531	0
Geogia	1	0	0.000000	51.4	4.90	13.4000	14.26288	0.89881	0
Geogia	2	0	0.000000	51.9	8.84	13.4000	14.23844	0.89881	0
Geogia	3	4585	8.430545	63.2	5.28	15.1245	14.21404	0.89881	0
Geogia	4	21510	9.976273	63.2	7.59	20.2970	14.18968	0.89881	0
Geogia	5	20914	9.948174	69.3	3.18	16.8480	14.16536	0.89881	0
Geogia	6	34282	10.442376	77.0	3.91	16.8480	14.14109	0.89881	0
Geogia	7	105061	11.562296	81.5	4.12	16.8480	14.11685	0.89881	0
Geogia	8	84119	11.339988	80.4	6.59	16.8480	14.09266	0.89881	0
Geogia	9	47555	10.769642	74.3	6.83	16.8480	14.06851	0.89881	0
Geogia	10	42764	10.663452	45.4	3.39	15.1245	14.28737	0.89881	0
Idaho	1	0	0.000000	27.4	3.93	10.8000	16.20983	0.46453	0
Idaho	2	0	0.000000	26.4	2.11	10.8000	16.15464	0.46453	0

state	month	cases	cases_log	avg_temp	precipitation	uninsured	older_pop	p_ratio	quarantine
Idaho	3	525	6.263398	35.2	2.00	10.8000	16.09963	0.46453	0
Idaho	4	1490	7.306531	41.6	1.42	17.6970	16.04481	0.46453	1
Idaho	5	824	6.714170	50.7	2.46	14.2480	15.99018	0.46453	1
Idaho	6	3278	8.094989	56.2	3.00	14.2480	15.93573	0.46453	0
Idaho	7	14604	9.589051	65.0	0.44	14.2480	15.88147	0.46453	0
Idaho	8	11367	9.338470	67.1	0.25	12.5245	15.82739	0.46453	0
Idaho	9	9960	9.206332	58.8	0.69	14.2480	15.77350	0.46453	0
Idaho	10	22560	10.023934	52.1	1.54	14.2480	16.26522	0.46453	0
Illinois	1	0	0.000000	31.9	4.37	7.4000	16.13281	1.43750	0
Illinois	2	0	0.000000	31.9	2.01	7.4000	16.14141	1.43750	0
Illinois	3	5992	8.698180	44.4	3.96	9.1245	16.15003	1.43750	0
Illinois	4	46924	10.756285	49.6	4.32	14.2970	16.15865	1.43750	0
Illinois	5	67342	11.117539	60.6	5.26	14.2970	16.16727	1.43750	0
Illinois	6	23978	10.084892	73.6	3.59	14.2970	16.17590	1.43750	0
Illinois	7	35880	10.487935	77.2	5.63	14.2970	16.18453	1.43750	0
Illinois	8	56607	10.943888	72.8	1.91	14.2970	16.19316	1.43750	0
Illinois	9	59038	10.985937	65.6	3.20	14.2970	16.20180	1.43750	0
Illinois	10	120796	11.701859	53.2	2.93	10.8480	16.12420	1.43750	0
Indiana	1	0	0.000000	34.3	4.65	8.7000	16.11678	0.66372	0
Indiana	2	0	0.000000	32.8	2.79	8.7000	16.10604	0.66372	0
Indiana	3	2159	7.677400	44.6	4.61	8.7000	16.09531	0.66372	0
Indiana	4	15676	9.659886	48.9	3.03	15.5970	16.08459	0.66372	0
Indiana	5	16739	9.725497	59.7	5.07	15.5970	16.07387	0.66372	0
Indiana	6	11020	9.307467	72.0	3.50	15.5970	16.06316	0.66372	0
Indiana	7	20560	9.931103	76.4	4.59	12.1480	16.05246	0.66372	0
Indiana	8	28042	10.241459	72.2	3.31	12.1480	16.04176	0.66372	0
Indiana	9	25823	10.159021	65.3	1.50	12.1480	16.03108	0.66372	0
Indiana	10	59339	10.991022	46.0	4.36	10.4245	16.12752	0.66372	0
Iowa	1	0	0.000000	23.1	1.37	5.0000	17.51481	0.81605	0
Iowa	2	0	0.000000	24.8	0.43	5.0000	17.50387	0.81605	0
Iowa	3	497	6.208590	40.3	2.90	5.0000	17.49294	0.81605	0
Iowa	4	6648	8.802071	46.7	1.64	11.8970	17.48201	0.81605	0
Iowa	5	12407	9.426016	57.6	4.56	11.8970	17.47109	0.81605	0
Iowa	6	9395	9.147933	72.9	4.93	8.4480	17.46018	0.81605	0
Iowa	7	15635	9.657267	75.4	2.90	8.4480	17.44928	0.81605	0
Iowa	8	20241	9.915465	71.9	1.22	8.4480	17.43838	0.81605	0
Iowa	9	24007	10.086101	61.9	4.06	6.7245	17.42749	0.81605	0
Iowa	10	39136	10.574798	52.6	1.66	6.7245	17.52576	0.81605	0
Kansas	1	0	0.000000	34.0	1.32	9.2000	16.32182	0.63523	0
Kansas	2	0	0.000000	34.8	1.29	9.2000	16.32236	0.63523	0
Kansas	3	428	6.059123	48.0	2.06	9.2000	16.32291	0.63523	1
Kansas	4	3810	8.245385	52.6	1.37	16.0970	16.32345	0.63523	1
Kansas	5	5481	8.609043	61.6	4.09	12.6480	16.32400	0.63523	1
Kansas	6	4724	8.460411	77.7	2.72	12.6480	16.32454	0.63523	1
Kansas	7	13369	9.500694	79.2	6.32	12.6480	16.32508	0.63523	1
Kansas	8	14800	9.602382	76.4	1.67	12.6480	16.32563	0.63523	1
Kansas	9	17137	9.748995	66.3	1.67	12.6480	16.32617	0.63523	1
Kansas	10	25432	10.143764	57.8	1.07	12.6480	16.32128	0.63523	1
Kentucky	1	0	0.000000	40.2	4.47	8.1245	16.79000	0.52320	0
Kentucky	2	0	0.000000	39.7	6.43	8.1245	16.78021	0.52320	0
Kentucky	3	591	6.381816	51.3	6.83	9.8480	16.77043	0.52320	1
Kentucky	4	4117	8.322880	52.8	4.94	13.2970	16.76065	0.52320	1

state	month	cases	cases_log	avg_temp	precipitation	uninsured	older_popp_ratio		quarantine
Kentucky	5	4996	8.516393	62.2	5.57	13.2970	16.75088	0.52320	1
Kentucky	6	5920	8.686092	72.6	5.15	8.1245	16.74112	0.52320	0
Kentucky	7	14527	9.583764	78.7	5.19	8.1245	16.73136	0.52320	0
Kentucky	8	18245	9.811646	74.8	5.22	9.8480	16.72160	0.52320	0
Kentucky	9	20444	9.925445	68.2	3.77	9.8480	16.71185	0.52320	0
Kentucky	10	38379	10.555266	68.4	4.60	9.8480	16.79980	0.52320	0
Louisiana	1	0	0.000000	53.7	7.56	12.3480	15.94430	0.66093	0
Louisiana	2	0	0.000000	54.1	5.81	12.3480	15.94855	0.66093	0
Louisiana	3	5237	8.563504	67.3	3.77	12.3480	15.95281	0.66093	0
Louisiana	4	22807	10.034823	66.6	6.34	15.7970	15.95706	0.66093	0
Louisiana	5	11872	9.381938	73.0	5.61	15.7970	15.96132	0.66093	0
Louisiana	6	18179	9.808022	79.7	5.27	12.3480	15.96558	0.66093	0
Louisiana	7	58185	10.971383	82.7	6.92	12.3480	15.96983	0.66093	0
Louisiana	8	32614	10.392497	82.3	6.07	12.3480	15.97409	0.66093	0
Louisiana	9	18564	9.828980	77.6	4.33	12.3480	15.97836	0.66093	0
Louisiana	10	19191	9.862197	44.8	5.70	12.3480	15.94005	0.66093	0
Maine	1	0	0.000000	20.8	3.06	8.0000	21.21238	1.06459	0
Maine	2	0	0.000000	20.0	2.85	8.0000	21.20266	1.06459	0
Maine	3	303	5.713733	29.7	2.70	8.0000	21.19295	1.06459	0
Maine	4	820	6.709304	37.8	4.16	14.8970	21.18324	1.06459	1
Maine	5	1226	7.111512	51.3	2.62	11.4480	21.17353	1.06459	1
Maine	6	945	6.851185	62.6	2.29	11.4480	21.16383	1.06459	1
Maine	7	643	6.466145	68.8	3.85	11.4480	21.15414	1.06459	1
Maine	8	611	6.415097	65.6	2.81	11.4480	21.14444	1.06459	1
Maine	9	883	6.783325	57.2	1.02	11.4480	21.13476	1.06459	1
Maine	10	1237	7.120444	59.4	5.86	11.4480	21.22210	1.06459	1
Maryland	1	0	0.000000	39.0	3.04	6.0000	15.86033	1.77876	0
Maryland	2	0	0.000000	40.8	3.19	6.0000	15.85148	1.77876	0
Maryland	3	1660	7.414573	49.2	2.91	6.0000	15.84263	1.77876	0
Maryland	4	21812	9.990216	51.6	4.88	12.8970	15.83379	1.77876	0
Maryland	5	29855	10.304108	60.5	3.07	9.4480	15.82496	1.77876	0
Maryland	6	14591	9.588160	72.7	3.61	9.4480	15.81612	1.77876	0
Maryland	7	21447	9.973340	80.1	4.23	9.4480	15.80730	1.77876	0
Maryland	8	19498	9.878067	76.8	9.01	9.4480	15.79848	1.77876	0
Maryland	9	16647	9.719985	67.4	3.85	9.4480	15.78966	1.77876	0
Maryland	10	20635	9.934744	52.5	4.29	9.4480	15.86918	1.77876	0
Massachusetts	1	0	0.000000	32.0	1.83	3.0000	16.94999	1.82927	0
Massachusetts	2	1	0.000000	32.5	3.31	3.0000	16.93475	1.82927	0
Massachusetts	3	6619	8.797700	40.2	3.72	3.0000	16.91952	1.82927	0
Massachusetts	4	55585	10.925669	43.1	5.36	9.8970	16.90431	1.82927	0
Massachusetts	5	34760	10.456223	56.2	2.50	9.8970	16.88911	1.82927	0
Massachusetts	6	11917	9.385721	67.6	2.53	20.2410	16.87392	1.82927	0
Massachusetts	7	8730	9.074521	74.5	2.93	9.8970	16.85875	1.82927	0
Massachusetts	8	10590	9.267665	71.7	2.70	9.8970	16.84359	1.82927	1
Massachusetts	9	11447	9.345483	62.7	2.20	6.4480	16.82844	1.82927	1
Massachusetts	10	24768	10.117308	44.3	5.06	6.4480	16.96524	1.82927	1
Michigan	1	0	0.000000	27.0	2.84	7.5245	17.67002	0.99366	0
Michigan	2	0	0.000000	23.6	1.03	7.5245	17.66281	0.99366	0
Michigan	3	7615	8.937875	35.0	2.83	7.5245	17.65560	0.99366	0
Michigan	4	33764	10.427150	40.2	3.01	23.0410	17.64839	0.99366	0
Michigan	5	16018	9.681468	53.2	4.05	23.0410	17.64119	0.99366	0
Michigan	6	13331	9.497847	65.8	3.09	12.6970	17.63399	0.99366	0

state	month	cases	cases_log	avg_temp	precipitation	uninsured	older_pop	p_ratio	quarantine
Michigan	7	19846	9.895758	72.4	3.96	9.2480	17.62679	0.99366	0
Michigan	8	22451	10.019090	68.5	3.82	9.2480	17.61959	0.99366	0
Michigan	9	24989	10.126191	58.1	3.09	9.2480	17.61240	0.99366	0
Michigan	10	59392	10.991915	38.8	3.67	9.2480	17.67723	0.99366	0
Minnesota	1	0	0.000000	14.0	0.87	4.9000	16.29826	1.03341	0
Minnesota	2	0	0.000000	14.0	0.34	4.9000	16.27670	1.03341	0
Minnesota	3	689	6.535241	30.4	1.19	4.9000	16.25516	1.03341	0
Minnesota	4	4447	8.399985	39.3	1.26	8.3480	16.23365	1.03341	0
Minnesota	5	20072	9.907081	53.5	2.07	8.3480	16.21217	1.03341	0
Minnesota	6	11508	9.350798	67.7	4.04	8.3480	16.19072	1.03341	0
Minnesota	7	18472	9.824011	71.4	4.92	8.3480	16.16929	1.03341	0
Minnesota	8	20676	9.936729	68.3	4.30	8.3480	16.14790	1.03341	0
Minnesota	9	23270	10.054920	56.5	1.47	8.3480	16.12653	1.03341	0
Minnesota	10	49338	10.806450	65.9	1.81	6.6245	16.31986	1.03341	0
Mississippi	1	0	0.000000	50.1	8.43	16.4480	16.35179	0.69257	0
Mississippi	2	0	0.000000	50.7	9.37	16.4480	16.35056	0.69257	0
Mississippi	3	1073	6.978214	64.0	6.22	16.4480	16.34933	0.69257	0
Mississippi	4	6139	8.722417	62.7	7.09	19.8970	16.34811	0.69257	0
Mississippi	5	8540	9.052516	70.0	3.54	19.8970	16.34688	0.69257	0
Mississippi	6	12148	9.404920	78.1	6.44	16.4480	16.34566	0.69257	0
Mississippi	7	31981	10.372897	82.0	6.04	16.4480	16.34443	0.69257	0
Mississippi	8	23703	10.073357	80.3	4.67	16.4480	16.34320	0.69257	0
Mississippi	9	15302	9.635739	75.5	3.76	16.4480	16.34198	0.69257	0
Mississippi	10	21614	9.981096	53.6	5.18	16.4480	16.35301	0.69257	0
Missouri	1	0	0.000000	34.6	4.43	10.0000	17.29423	0.67199	0
Missouri	2	0	0.000000	35.4	2.51	10.0000	17.28415	0.67199	0
Missouri	3	1327	7.190676	48.8	5.52	11.7245	17.27407	0.67199	0
Missouri	4	6235	8.737934	53.1	3.95	16.8970	17.26400	0.67199	0
Missouri	5	5585	8.627840	62.0	6.23	16.8970	17.25393	0.67199	0
Missouri	6	8404	9.036463	75.1	3.63	13.4480	17.24388	0.67199	0
Missouri	7	28772	10.267158	79.2	5.79	13.4480	17.23382	0.67199	0
Missouri	8	34374	10.445056	74.2	2.90	13.4480	17.22378	0.67199	0
Missouri	9	41416	10.631423	67.2	3.03	11.7245	17.21373	0.67199	0
Missouri	10	59422	10.992420	39.4	3.70	11.7245	17.30432	0.67199	0
Montana	1	0	0.000000	23.4	1.20	8.3000	19.27857	0.63669	0
Montana	2	0	0.000000	25.5	1.22	8.3000	19.24169	0.63669	0
Montana	3	203	5.313206	31.5	0.94	10.0245	19.20488	0.63669	1
Montana	4	250	5.521461	38.2	1.16	15.1970	19.16814	0.63669	1
Montana	5	62	4.127134	50.6	2.48	11.7480	19.13147	0.63669	1
Montana	6	503	6.220590	59.3	3.42	11.7480	19.09487	0.63669	1
Montana	7	2947	7.988543	65.7	1.09	11.7480	19.05834	0.63669	0
Montana	8	3528	8.168486	67.4	0.47	11.7480	19.02188	0.63669	0
Montana	9	5900	8.682708	57.1	0.93	11.7480	18.98550	0.63669	0
Montana	10	19408	9.873441	46.5	2.10	10.0245	19.31552	0.63669	0
Nebraska	1	0	0.000000	27.2	0.59	8.3000	16.13647	0.57411	0
Nebraska	2	0	0.000000	29.6	0.25	8.3000	16.12022	0.57411	0
Nebraska	3	177	5.176150	41.2	1.91	10.0245	16.10398	0.57411	0
Nebraska	4	4104	8.319717	46.0	0.75	11.7480	16.08776	0.57411	0
Nebraska	5	9820	9.192176	56.8	4.05	11.7480	16.07155	0.57411	0
Nebraska	6	5076	8.532279	73.5	2.56	11.7480	16.05537	0.57411	0
Nebraska	7	7034	8.858511	75.3	4.10	10.0245	16.03919	0.57411	0
Nebraska	8	8076	8.996652	74.1	0.92	10.0245	16.02304	0.57411	0

state	month	cases	cases_log	avg_temp	precipitation	uninsured	older_pop	p_ratio	quarantine
Nebraska	9	11277	9.330521	62.7	1.02	10.0245	16.00690	0.57411	0
Nebraska	10	25168	10.133329	55.4	0.56	8.3000	16.15275	0.57411	0
Nevada	1	0	0.000000	35.2	0.70	13.1245	16.05568	1.05275	0
Nevada	2	0	0.000000	36.2	0.38	13.1245	16.00939	1.05275	0
Nevada	3	1113	7.014814	40.4	1.27	14.8480	15.96322	1.05275	0
Nevada	4	3894	8.267192	48.7	0.65	28.6410	15.91720	1.05275	0
Nevada	5	3603	8.189522	58.8	0.63	28.6410	15.87130	1.05275	0
Nevada	6	10074	9.217713	65.0	0.55	18.2970	15.82554	1.05275	0
Nevada	7	29628	10.296475	74.2	0.11	18.2970	15.77991	1.05275	0
Nevada	8	21172	9.960435	75.6	0.12	18.2970	15.73441	1.05275	0
Nevada	9	10601	9.268704	66.6	0.07	18.2970	15.68904	1.05275	0
Nevada	10	20678	9.936826	47.1	0.10	18.2970	16.10211	1.05275	0
New Hampshire	1	0	0.000000	25.1	2.75	6.3000	18.65320	1.00645	0
New Hampshire	2	0	0.000000	24.2	3.36	6.3000	18.63627	1.00645	0
New Hampshire	3	367	5.905362	34.1	3.08	6.3000	18.61936	1.00645	0
New Hampshire	4	1779	7.483807	39.6	4.79	13.1970	18.60246	1.00645	0
New Hampshire	5	2505	7.826044	53.5	2.73	13.1970	18.58558	1.00645	0
New Hampshire	6	1131	7.030857	63.9	2.45	9.7480	18.56871	1.00645	0
New Hampshire	7	801	6.685861	71.2	4.57	9.7480	18.55186	1.00645	0
New Hampshire	8	692	6.539586	66.7	2.65	9.7480	18.53503	1.00645	0
New Hampshire	9	991	6.898714	58.6	1.77	9.7480	18.51821	1.00645	0
New Hampshire	10	2818	7.943783	57.2	5.28	8.0245	18.67014	1.00645	0
New Jersey	1	0	0.000000	37.2	2.31	9.6245	16.60805	1.34146	0
New Jersey	2	0	0.000000	39.0	2.78	9.6245	16.60376	1.34146	0
New Jersey	3	18696	9.836065	46.3	3.68	9.6245	16.59948	1.34146	0
New Jersey	4	99956	11.512485	48.6	4.01	14.7970	16.59519	1.34146	0
New Jersey	5	41793	10.640484	59.0	2.47	14.7970	16.59090	1.34146	0
New Jersey	6	11222	9.325631	71.4	2.92	14.7970	16.58662	1.34146	1
New Jersey	7	9993	9.209640	78.7	6.76	14.7970	16.58233	1.34146	1
New Jersey	8	10300	9.239899	75.4	6.15	14.7970	16.57805	1.34146	1
New Jersey	9	13315	9.496647	66.8	4.48	11.3480	16.57377	1.34146	1
New Jersey	10	32611	10.392405	56.7	5.15	11.3480	16.61234	1.34146	1
New Mexico	1	0	0.000000	37.0	0.52	11.7245	18.00772	1.20750	0
New Mexico	2	0	0.000000	38.4	0.81	11.7245	18.00682	1.20750	0
New Mexico	3	315	5.752573	48.0	1.19	13.4480	18.00592	1.20750	1
New Mexico	4	3096	8.037866	53.9	0.19	16.8970	18.00502	1.20750	1
New Mexico	5	4278	8.361241	65.0	0.20	13.4480	18.00412	1.20750	1

state	month	cases	cases_log	avg_temp	precipitation	uninsured	older_pop	p_ratio	quarantine
New Mexico	6	4458	8.402456	72.3	0.48	13.4480	18.00322	1.20750	1
New Mexico	7	8453	9.042277	76.5	2.20	16.8970	18.00232	1.20750	1
New Mexico	8	4752	8.466321	76.0	0.72	16.8970	18.00142	1.20750	1
New Mexico	9	4083	8.314587	65.3	0.74	13.4480	18.00052	1.20750	1
New Mexico	10	17055	9.744199	49.1	0.65	13.4480	18.00862	1.20750	1
New York	1	0	0.000000	27.7	2.78	6.9245	16.95103	1.61644	0
New York	2	0	0.000000	26.6	3.03	6.9245	16.95838	1.61644	0
New York	3	74427	11.217574	37.2	2.89	6.9245	16.96573	1.61644	0
New York	4	224679	12.322428	41.1	3.13	12.0970	16.97309	1.61644	0
New York	5	73916	11.210685	54.1	3.04	12.0970	16.98044	1.61644	0
New York	6	22272	10.011086	65.2	2.38	12.0970	16.98781	1.61644	1
New York	7	21339	9.968292	72.9	4.10	12.0970	16.99517	1.61644	1
New York	8	19150	9.860058	68.4	4.61	12.0970	17.00254	1.61644	1
New York	9	24287	10.097696	59.6	2.59	8.6480	17.00991	1.61644	1
New York	10	50829	10.836222	63.3	3.92	8.6480	16.94368	1.61644	1
North Carolina	1	0	0.000000	46.1	4.37	13.0245	16.66544	0.92771	0
North Carolina	2	0	0.000000	47.1	7.01	13.0245	16.63494	0.92771	0
North Carolina	3	1498	7.311886	56.0	3.31	13.0245	16.60450	0.92771	0
North Carolina	4	9011	9.106201	57.5	5.28	18.1970	16.57412	0.92771	0
North Carolina	5	18081	9.802617	63.6	7.62	18.1970	16.54379	0.92771	0
North Carolina	6	36147	10.495349	73.3	5.04	14.7480	16.51351	0.92771	0
North Carolina	7	58344	10.974112	79.7	4.17	14.7480	16.48329	0.92771	0
North Carolina	8	47003	10.757967	77.6	8.01	14.7480	16.45313	0.92771	0
North Carolina	9	40548	10.610242	69.8	6.75	14.7480	16.42302	0.92771	0
North Carolina	10	64003	11.066685	37.6	4.26	14.7480	16.69600	0.92771	0
North Dakota	1	0	0.000000	12.9	0.38	6.9000	15.72418	0.43175	0
North Dakota	2	0	0.000000	17.8	0.17	6.9000	15.72130	0.43175	0
North Dakota	3	126	4.836282	29.8	0.24	6.9000	15.71842	0.43175	1
North Dakota	4	941	6.846943	37.6	0.80	10.3480	15.71554	0.43175	1
North Dakota	5	1510	7.319865	52.5	1.39	10.3480	15.71266	0.43175	1
North Dakota	6	999	6.906755	67.0	2.48	10.3480	15.70978	0.43175	0

state	month	cases	cases_log	avg_temp	precipitation	uninsured	older_pop	p_ratio	quarantine
North Dakota	7	3026	8.014997	70.4	3.95	10.3480	15.70690	0.43175	0
North Dakota	8	5398	8.593784	69.1	2.07	8.6245	15.70402	0.43175	0
North Dakota	9	10218	9.231906	57.0	0.51	8.6245	15.70114	0.43175	0
North Dakota	10	22825	10.035612	53.6	0.62	8.6245	15.72707	0.43175	0
Ohio	1	0	0.000000	34.9	3.51	8.3245	17.49893	0.84211	0
Ohio	2	0	0.000000	32.7	2.98	8.3245	17.49164	0.84211	0
Ohio	3	2199	7.695758	44.6	4.98	10.0480	17.48436	0.84211	0
Ohio	4	15828	9.669536	47.7	3.66	23.8410	17.47708	0.84211	0
Ohio	5	17486	9.769156	58.3	5.11	13.4970	17.46980	0.84211	0
Ohio	6	16276	9.697447	70.3	3.12	13.4970	17.46252	0.84211	0
Ohio	7	39370	10.580759	76.8	3.13	10.0480	17.45525	0.84211	0
Ohio	8	31998	10.373429	72.2	3.71	10.0480	17.44798	0.84211	0
Ohio	9	30830	10.336244	64.7	3.11	10.0480	17.44071	0.84211	0
Ohio	10	61710	11.030201	57.4	4.07	10.0480	17.50622	0.84211	0
Oklahoma	1	0	0.000000	42.2	3.59	14.3000	16.04690	0.44257	0
Oklahoma	2	0	0.000000	41.7	1.83	14.3000	16.04289	0.44257	0
Oklahoma	3	565	6.336826	55.4	5.16	14.3000	16.03888	0.44257	1
Oklahoma	4	3053	8.023880	57.9	2.93	21.1970	16.03487	0.44257	1
Oklahoma	5	2662	7.886833	67.2	5.05	21.1970	16.03087	0.44257	1
Oklahoma	6	6937	8.844625	78.8	2.10	17.7480	16.02686	0.44257	0
Oklahoma	7	25888	10.161535	82.5	4.75	17.7480	16.02285	0.44257	0
Oklahoma	8	25003	10.126751	79.4	2.80	17.7480	16.01885	0.44257	0
Oklahoma	9	29334	10.286502	70.2	4.36	17.7480	16.01484	0.44257	0
Oklahoma	10	35749	10.484278	51.4	3.12	17.7480	16.05091	0.44257	0
Oregon	1	0	0.000000	35.0	6.75	7.2000	18.12357	1.28133	0
Oregon	2	1	0.000000	35.9	2.18	7.2000	18.08394	1.28133	0
Oregon	3	689	6.535241	38.8	2.41	7.2000	18.04439	1.28133	0
Oregon	4	1820	7.506592	46.4	1.38	14.0970	18.00493	1.28133	0
Oregon	5	1733	7.457609	52.6	3.00	14.0970	17.96556	1.28133	0
Oregon	6	4413	8.392310	57.9	2.01	14.0970	17.92627	1.28133	0
Oregon	7	9837	9.193906	66.0	0.13	14.0970	17.88707	1.28133	0
Oregon	8	8220	9.014325	67.2	0.16	10.6480	17.84795	1.28133	0
Oregon	9	6796	8.824089	62.8	0.91	10.6480	17.80892	1.28133	0
Oregon	10	11412	9.342421	52.3	1.50	10.6480	18.16329	1.28133	0
Pennsylvania	1	0	0.000000	32.2	3.03	7.5245	18.69351	0.98548	0
Pennsylvania	2	0	0.000000	33.2	3.35	7.5245	18.69179	0.98548	0
Pennsylvania	3	4843	8.485290	42.5	4.28	9.2480	18.69008	0.98548	0
Pennsylvania	4	40920	10.619374	45.1	4.51	12.6970	18.68837	0.98548	0
Pennsylvania	5	26519	10.185617	56.0	3.47	12.6970	18.68665	0.98548	0
Pennsylvania	6	14960	9.613135	67.3	3.16	12.6970	18.68494	0.98548	0
Pennsylvania	7	25694	10.154013	74.8	3.58	12.6970	18.68323	0.98548	0
Pennsylvania	8	21089	9.956507	71.5	4.38	12.6970	18.68152	0.98548	0
Pennsylvania	9	24942	10.124308	62.1	2.47	9.2480	18.67980	0.98548	0
Pennsylvania	10	49060	10.800799	54.6	3.66	9.2480	18.69522	0.98548	0
Rhode Island	1	0	0.000000	35.4	1.50	4.1000	17.65849	1.39846	0
Rhode Island	2	0	0.000000	35.4	3.30	4.1000	17.66011	1.39846	0

state	month	cases	cases_log	avg_temp	precipitation	uninsured	older_pop	p_ratio	quarantine
Rhode Island	3	520	6.253829	42.6	4.46	5.8245	17.66173	1.39846	1
Rhode Island	4	8101	8.999743	44.0	5.40	21.3410	17.66335	1.39846	1
Rhode Island	5	6307	8.749415	56.6	3.17	10.9970	17.66497	1.39846	1
Rhode Island	6	1885	7.541683	68.1	2.84	10.9970	17.66658	1.39846	1
Rhode Island	7	2209	7.700295	75.5	1.73	10.9970	17.66820	1.39846	1
Rhode Island	8	2927	7.981733	73.7	1.78	10.9970	17.66982	1.39846	1
Rhode Island	9	2799	7.937017	64.5	1.17	10.9970	17.67144	1.39846	1
Rhode Island	10	8126	9.002824	67.6	5.53	7.5480	17.65687	1.39846	1
South Carolina	1	0	0.000000	50.4	4.12	10.8000	18.16157	0.74135	0
South Carolina	2	0	0.000000	50.9	7.17	10.8000	18.12412	0.74135	0
South Carolina	3	1083	6.987490	60.5	4.26	10.8000	18.08674	0.74135	1
South Carolina	4	5012	8.519590	62.3	5.14	17.6970	18.04944	0.74135	1
South Carolina	5	5766	8.659734	68.1	6.64	17.6970	18.01221	0.74135	1
South Carolina	6	24538	10.107978	76.2	4.27	14.2480	17.97506	0.74135	0
South Carolina	7	52617	10.870795	81.9	4.69	14.2480	17.93799	0.74135	0
South Carolina	8	29976	10.308152	80.2	6.95	14.2480	17.90099	0.74135	0
South Carolina	9	28950	10.273326	73.4	6.17	14.2480	17.86408	0.74135	0
South Carolina	10	28670	10.263607	41.2	2.66	12.5245	18.19911	0.74135	0
South Dakota	1	0	0.000000	20.0	0.41	10.2000	17.13337	0.51545	0
South Dakota	2	0	0.000000	23.5	0.42	10.2000	17.09974	0.51545	0
South Dakota	3	108	4.682131	36.3	0.78	10.2000	17.06618	0.51545	0
South Dakota	4	2341	7.758333	41.9	0.94	17.0970	17.03268	0.51545	0
South Dakota	5	2544	7.841493	54.2	2.72	13.6480	16.99925	0.51545	0
South Dakota	6	1771	7.479300	70.2	3.04	13.6480	16.96588	0.51545	0
South Dakota	7	2000	7.600903	73.6	3.34	13.6480	16.93258	0.51545	0
South Dakota	8	4745	8.464847	72.7	1.96	11.9245	16.89935	0.51545	0

state	month	cases	cases_log	avg_temp	precipitation	uninsured	older_pop	p_ratio	quarantine
South Dakota	9	8880	9.091557	60.7	0.76	11.9245	16.86618	0.51545	0
South Dakota	10	23603	10.069129	60.5	1.09	11.9245	17.16707	0.51545	0
Tennessee	1	0	0.000000	43.0	6.73	10.1000	16.71654	0.57166	0
Tennessee	2	0	0.000000	43.4	9.18	10.1000	16.69039	0.57166	0
Tennessee	3	2239	7.713785	54.8	8.14	10.1000	16.66428	0.57166	0
Tennessee	4	8496	9.047351	55.4	6.56	16.9970	16.63822	0.57166	0
Tennessee	5	12424	9.427385	64.0	4.56	16.9970	16.61219	0.57166	0
Tennessee	6	20350	9.920836	73.5	3.86	13.5480	16.58621	0.57166	0
Tennessee	7	62450	11.042122	79.3	4.73	13.5480	16.56026	0.57166	0
Tennessee	8	48974	10.799045	76.4	5.90	13.5480	16.53436	0.57166	0
Tennessee	9	41206	10.626339	69.8	4.54	13.5480	16.50849	0.57166	0
Tennessee	10	64533	11.074932	65.9	4.88	13.5480	16.74273	0.57166	0
Texas	1	0	0.000000	50.7	1.95	18.4000	12.84979	0.82759	0
Texas	2	0	0.000000	49.4	1.90	18.4000	12.82115	0.82759	0
Texas	3	3266	8.091321	63.2	3.17	21.8480	12.79258	0.82759	1
Texas	4	24821	10.119445	65.0	1.88	25.2970	12.76408	0.82759	1
Texas	5	36200	10.496814	74.5	3.58	25.2970	12.73563	0.82759	1
Texas	6	95699	11.468963	80.6	2.15	21.8480	12.70725	0.82759	0
Texas	7	260960	12.472122	85.2	2.22	21.8480	12.67894	0.82759	0
Texas	8	192023	12.165370	84.3	1.33	21.8480	12.65068	0.82759	0
Texas	9	135998	11.820396	74.1	4.05	21.8480	12.62249	0.82759	0
Texas	10	151629	11.929192	52.4	0.96	21.8480	12.87848	0.82759	0
Utah	1	0	0.000000	28.5	0.72	9.7000	11.37588	0.60310	0
Utah	2	0	0.000000	30.8	0.70	9.7000	11.33969	0.60310	0
Utah	3	934	6.839476	40.5	1.63	11.4245	11.30361	0.60310	0
Utah	4	3819	8.247744	47.2	0.58	16.5970	11.26765	0.60310	1
Utah	5	5191	8.554682	58.8	0.33	13.1480	11.23180	0.60310	1
Utah	6	12802	9.457357	65.4	0.93	13.1480	11.19607	0.60310	1
Utah	7	18051	9.800956	73.6	0.38	11.4245	11.16045	0.60310	0
Utah	8	11995	9.392245	75.7	0.12	11.4245	11.12494	0.60310	0
Utah	9	20250	9.915910	63.8	0.21	11.4245	11.08954	0.60310	0
Utah	10	41614	10.636192	46.4	0.19	11.4245	11.41219	0.60310	0
Vermont	1	0	0.000000	23.4	2.83	4.5000	20.03414	1.87129	0
Vermont	2	0	0.000000	22.4	3.23	4.5000	20.02947	1.87129	0
Vermont	3	293	5.680173	33.0	2.93	4.5000	20.02479	1.87129	1
Vermont	4	573	6.350886	38.8	3.94	11.3970	20.02012	1.87129	1
Vermont	5	115	4.744932	52.7	2.95	11.3970	20.01545	1.87129	1
Vermont	6	227	5.424950	62.9	2.37	7.9480	20.01078	1.87129	1
Vermont	7	206	5.327876	70.9	4.05	7.9480	20.00612	1.87129	1
Vermont	8	215	5.370638	65.4	4.34	6.2245	20.00145	1.87129	1
Vermont	9	126	4.836282	57.4	2.66	6.2245	19.99678	1.87129	1
Vermont	10	402	5.996452	59.2	4.44	4.5000	20.03881	1.87129	1
Virginia	1	0	0.000000	40.7	3.53	7.9000	15.90382	1.12162	0
Virginia	2	0	0.000000	42.5	5.01	7.9000	15.88700	1.12162	0
Virginia	3	1484	7.302496	51.7	2.91	7.9000	15.87021	1.12162	0
Virginia	4	15417	9.643226	53.4	5.97	14.7970	15.85343	1.12162	0
Virginia	5	28497	10.257554	60.5	4.87	11.3480	15.83667	1.12162	0
Virginia	6	17389	9.763593	71.3	5.12	11.3480	15.81993	1.12162	0
Virginia	7	28014	10.240460	78.8	4.06	11.3480	15.80320	1.12162	0
Virginia	8	30814	10.335724	75.5	8.20	11.3480	15.78649	1.12162	0

state	month	cases	cases_log	avg_temp	precipitation	uninsured	older_pop	p_ratio	quarantine
Virginia	9	27106	10.207510	66.4	6.15	11.3480	15.76980	1.12162	0
Virginia	10	33672	10.424422	48.3	5.02	11.3480	15.92065	1.12162	0
Washinton	1	0	0.000000	34.2	10.51	8.3245	15.84043	1.42663	0
Washinton	2	6	1.791759	35.6	4.92	8.3245	15.79476	1.42663	0
Washinton	3	4889	8.494743	38.3	2.83	10.0480	15.74922	1.42663	0
Washinton	4	9431	9.151757	46.1	1.38	13.4970	15.70381	1.42663	0
Washinton	5	7375	8.905851	53.3	3.51	13.4970	15.65853	1.42663	0
Washinton	6	11122	9.316680	57.9	2.39	10.0480	15.61338	1.42663	0
Washinton	7	22979	10.042336	64.7	0.37	13.4970	15.56836	1.42663	0
Washinton	8	18832	9.843313	65.7	0.46	10.0480	15.52347	1.42663	0
Washinton	9	12887	9.463974	61.4	2.41	10.0480	15.47871	1.42663	0
Washinton	10	19979	9.902437	55.3	4.08	10.0480	15.88624	1.42663	0
West Virginia	1	0	0.000000	37.2	3.68	8.4245	20.50510	0.38586	0
West Virginia	2	0	0.000000	38.0	5.27	8.4245	20.53145	0.38586	0
West Virginia	3	162	5.087596	47.8	4.03	10.1480	20.55784	0.38586	1
West Virginia	4	963	6.870053	48.9	6.56	13.5970	20.58425	0.38586	1
West Virginia	5	885	6.785588	57.8	5.69	13.5970	20.61070	0.38586	1
West Virginia	6	895	6.796824	68.0	5.24	13.5970	20.63719	0.38586	0
West Virginia	7	3737	8.226038	75.5	4.33	10.1480	20.66370	0.38586	0
West Virginia	8	3608	8.190909	72.3	5.66	10.1480	20.69026	0.38586	0
West Virginia	9	5598	8.630165	64.0	2.90	10.1480	20.71684	0.38586	0
West Virginia	10	8612	9.060912	41.3	3.46	10.1480	20.47879	0.38586	0
Wisconsin	1	0	0.000000	21.6	1.34	5.7000	17.46144	0.98517	0
Wisconsin	2	0	0.000000	19.2	0.69	5.7000	17.45184	0.98517	0
Wisconsin	3	1351	7.208600	34.3	3.04	5.7000	17.44225	0.98517	0
Wisconsin	4	5503	8.613049	40.8	2.27	12.5970	17.43266	0.98517	0
Wisconsin	5	11549	9.354354	54.1	3.96	12.5970	17.42308	0.98517	0
Wisconsin	6	13259	9.492432	66.6	4.99	9.1480	17.41350	0.98517	0
Wisconsin	7	25272	10.137452	72.0	5.54	9.1480	17.40393	0.98517	0
Wisconsin	8	23634	10.070442	68.3	3.27	9.1480	17.39436	0.98517	0
Wisconsin	9	48555	10.790453	57.3	3.23	9.1480	17.38480	0.98517	0
Wisconsin	10	108747	11.596779	41.5	2.96	9.1480	17.47104	0.98517	0
Wyoming	1	0	0.000000	23.9	1.01	14.0245	17.16313	0.32111	0
Wyoming	2	0	0.000000	20.2	1.21	14.0245	17.18963	0.32111	0
Wyoming	3	120	4.787492	33.0	1.03	14.0245	17.21617	0.32111	0
Wyoming	4	439	6.084499	37.5	1.32	15.7480	17.24275	0.32111	1
Wyoming	5	344	5.840642	50.3	1.24	15.7480	17.26937	0.32111	1
Wyoming	6	584	6.369901	59.6	1.67	15.7480	17.29604	0.32111	0
Wyoming	7	1239	7.122060	66.6	0.69	15.7480	17.32275	0.32111	0
Wyoming	8	1116	7.017506	67.9	0.31	15.7480	17.34949	0.32111	0
Wyoming	9	2106	7.652546	55.7	0.77	15.7480	17.37628	0.32111	0
Wyoming	10	7350	8.902456	66.8	1.03	15.7480	17.13667	0.32111	0