

Correlations to COVID-19 Deaths in California

Nic James, Sri Chandu, Thomas Li

05/12/2020

Contents

Abstract	3
Problem and Motivation	3
Data Description	3
Questions of Interest	4
Regression Analysis, Results and Interpretation	5
Important Details	5
Exploratory Analysis:	5
Diagnostic Checks:	7
Interpretation:	8
Conclusions	8
Appendices	9
Appendix 1: R Code for Original COVID-19 Data Set	9
Appendix 2a: R Code for Google Mobility + Categorical Variables	21
Appendix 2b: R Code for Google Mobility Only	26
Appendix 3: R Code for World Bank	37
Appendix 4: Exploratory analysis not used in final paper	40
Appendix 5: Data Variable Description	40
Source	41
References	41

Abstract

We looked at data collected for the COVID-19 pandemic combined with movement tracking collected by Google to see if we could determine which policy measure showed the most promise in effecting deaths from COVID-19 using multiple linear regression. We started by analyzing the data using only the COVID-19 data set but could not find a linear regression that worked. So we decided to use predictors solely from the Google Mobility data to see there were any linear correlations with death from COVID-19. We found that movement to residential, retail and recreational areas were correlated with an increase in deaths and that movement to grocery, pharmacy, parks, workplaces, and transit stations was correlated with a decrease in deaths.

Problem and Motivation

This past year our lives have changed drastically. We started school online instead of in person and have spent the majority of our year indoors, staying away from friends and family. We all know someone who has lost their lives to COVID-19 and we have experienced the effects of the virus daily. We wanted to use this data set because we were specifically interested in the Public Health measures like gathering restrictions, schools closing, workplace closing, and contact tracing during this pandemic. We wanted to see if we could find proof of how effective they were. We are hoping that by analyzing this data we will have a better understanding of which Public Health measures work the best. On a larger scale, analyses like this one will be extremely useful for future predictions and pandemics. Life styles and transportation have changed dramatically since the last worldwide pandemic and that was a hundred years ago. Having a recent event will help medical professionals to better understand the spread of this disease and hopefully make quicker and more effective decisions if this situation were to occur again in the future.

Data Description

This data set is a collection of governmental sources at national, regional, and city levels from 190 countries for COVID19. It includes time series of vaccines, test, cases, deaths, recovered, intensive therapy, and policy measures by Oxford COVID-19 Government Response Tracker. We will used the World Bank Google Mobility Reports as well. There are 16 variables in the base data set that we will be using for our regression. We will be limiting the location data strictly to California and using data from 3/15/2020 - 3/15/2021.

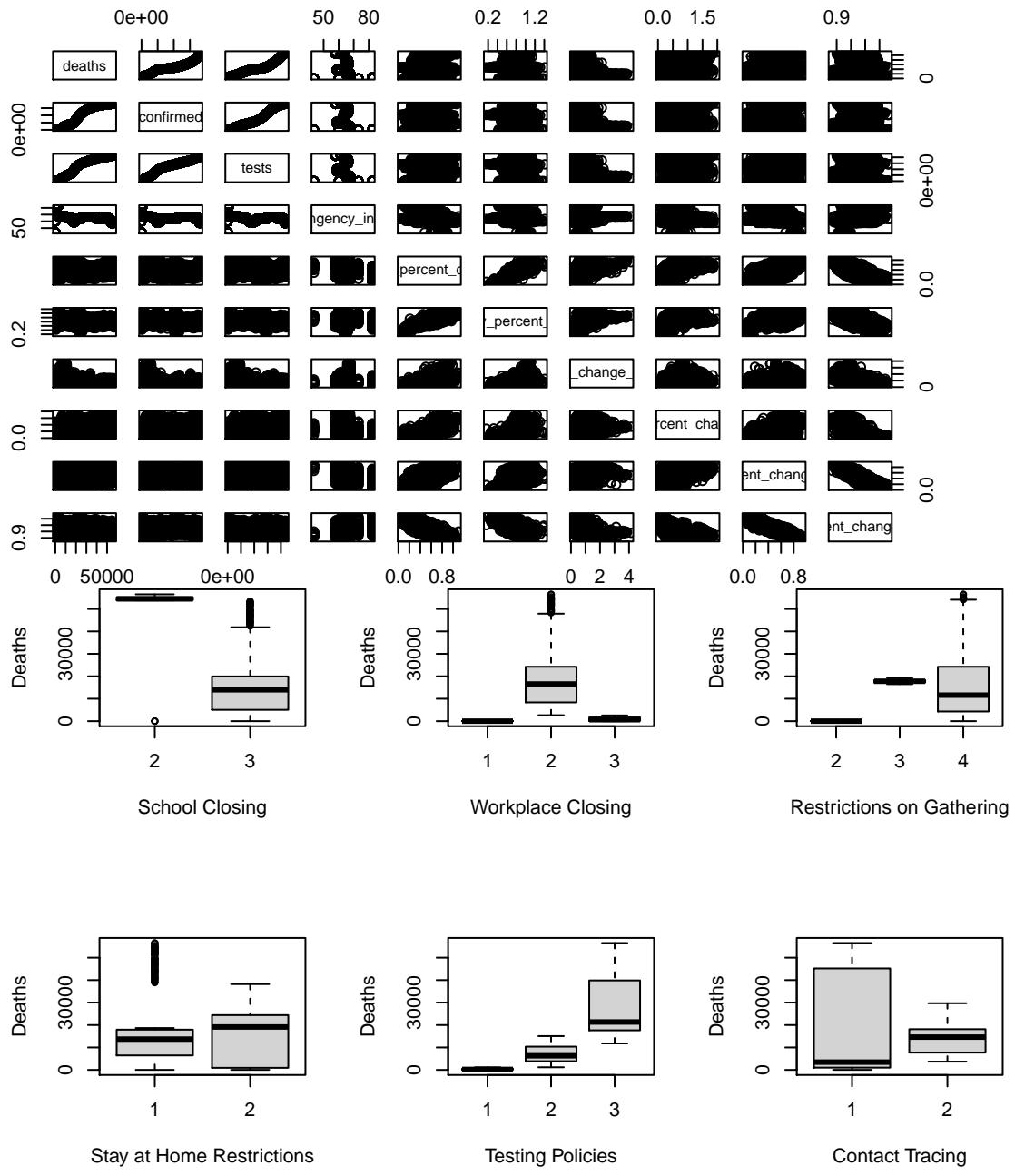
Our initial objective was to find out if running a linear regression of the Google Mobility data with the COVID-19 data had any significance in predicting the rate of deaths due to COVID-19. The Google mobility data recorded travel trends to categorized locations during the COVID-19 pandemic. This data is compared against a baseline reading; that is, the median value of each day of the week during a 5-week period (Jan 3 – Feb 6, 2020).

Variables used (for more details see Appendix 5):

Original COVID-19 data: date, confirmed, tests, population, latitude, longitude, school_closing, workplace_closing, cancel_events, transport_closing, stay_home_restrictions, internal_movement_restrictions, international_movement_restrictions, information_campaigns, testing_policy, contact_tracing, stringency_index

World Bank data set: GDP per capita, GDP per capita growth, Poverty rate, Pollution in mcg

Google Mobility data set: retail_and_recreation_percent_change_from_baseline, grocery_and_pharmacy_percent_change_from_baseline, parks_percent_change_from_baseline, transit_stations_percent_change_from_baseline, workplaces_percent_change_from_baseline, residential_percent_change_from_baseline



Questions of Interest

- What variables from the original data set have the most effect on deaths? We plan to use *deaths* as the response and *confirmed*, *tests*, *population*, *latitude*, *longitude*, *school_closing*, *workplace_closing*, *cancel_events*, *transport_closing*, *stay_home_restrictions*, *internal_movement_restrictions*, *international_movement_restrictions*, *information_campaigns*, *testing_policy*, *contact_tracing*, *stringency_index* from in the original COVID-19 data set as predictors to answer this question.
- Are the trends in movement significantly correlated to deaths caused by COVID-19? We plan to use *deaths* as the response; *confirmed*, *tests*, *contact tracing*, and *stringency index* from in the original COVID-19 data set; and *retail and recreation percent change from baseline*, *grocery and pharmacy percent*

change from baseline, parks percent change from baseline, transit stations percent change from baseline, workplaces percent change from baseline, residential percent change from baseline from the Google Mobility data set to answer this question.

3. How does the economic profile of the country affect the mortality rate from COVID over the year 2020? What is the effect of air pollution (or exposure to air pollution) to the number of cases and the mortality rate from COVID? We plan to use *deaths* as the response; *confirmed, tests, contact tracing*, and *stringency index* from in the original COVID-19 data set; and *GDP, GDP per capita growth, Hospital beds per 1000, Poverty headcount Ratio, CO2 emissions per capita, Percentage of population exposed to high air pollution level, Annual percent Inflation, Total Reserves, Prevalence of Undernourishment, and Annual mean Air Pollution Exposure* from the World Bank data set to answer these questions.

Regression Analysis, Results and Interpretation

Important Details

In our last analysis, we wanted to see if we could find a linear regression of the Google Mobility variables when deaths as a response. So, we started off by doing an initial summary, and our initial plots also showed that linearity assumptions were not satisfied. It also showed that Workplace change was not significant, which was interesting since we assumed that most workplaces were closed. Because the current model did not meet our assumptions of linearity, we decided to run a variable selection to help us narrow down significant predictors. We compared all models by looking at adjusted R-squared and CP values. (Table 2, Appendix 2B) The model we chose had all 6 predictor variables. Next, we decided to check if there were any necessary transformations for the predictors. We found that 5 out of 6 variables needed to be transformed.(Table 3, Appendix 2B).The assumptions were still not met (Plot 2, Appendix 2B). Then we needed to see if the Response variable needed to be transformed, and found that it required a square root transformation (Plot 3, Appendix 2B). Prior to transformation, when we did model selection using *reg.susbt*, we found that the CP and BIC indicated the 5 predictor model was better, but when we looked at the difference in Adjusted R² between the 6 vs. 5 predictor model, we found that they were very similar, at 34.328642 vs. 34.328653.

```
## [1] 5  
## [1] 6
```

Exploratory Analysis:

We started by creating a data frame by filtering the data by California, and then by date. We ended with 365 rows of data for California. There is not any data for *vaccines, recovered, hosp, vent, and icu* so we removed these variables. We decided to use the following variables to create a new data frame date using the original COVID-19 data. We then turned the policy measures (categorical variables) into factors before we fitted a regression model. However factors need to have 2 or more levels in order to work so we also removed *cancel_events, international_movement, and transport_closing*. We also removed all variables that caused a singularity in the data. This left us with a base data set of *confirmed, tests, fschool_closing, fworkplace_closing, fgatherings_restrictions, fstay_home_restrictions, ftesting_policy, fcontact_tracing, and stringency_index* as the predictors to start looking for a linear regression model with.

We started by running a hypothesis test to see if we would prefer the null model against the full model. From Table 1 in Appendix 1, we can see that the p-value is < 2.2e-16 so we reject the null model as at least one predictor in the full model is significant.

Next we looked at the scatter plots for all of the variables. This was less useful since there were so many plots that it was difficult to see in detail (Plot 1, Appendix 1) so we looked at the scatter plots of the

numerical data (Plot 2, Appendix 1) to see if there was anything that we could derive from the data. We assume that *confirmed* and *tests* would be a positive influence on the number of *deaths* because we see that there are positive linear relationships. The *stringency index* has a clear patterning to it that does not show any linear trends making it difficult to make any assumptions about it. We also should note that none of the variables are spread out. The data creates a line with the data points we will definitely need to transform this data to see if we can find a linear relationship. We then did an analysis of the categorical data using box plots (Plot 3, Appendix 1). From these we concluded that none of these variables have a constant variance and thus we will probably need to transform some if not all of the variables. We also looked at the added variable plots (Plot 4, Appendix 1) and summary to see if we should remove any variables. From the added variable plots we assumed that we will probably remove *testing policy*, *confirmed*, and *stringency index*. While *gathering restrictions 2* and *gathering restrictions 3* look like they should be removed, *gathering restrictions 4* looks to have some influence and therefore we chose to keep the *gathering restrictions*. However, the summary table shows us that *confirmed* and *gathering restrictions* will probably be removed. Which goes against what we previously thought when looking at only the scatter plots and the added variable plots. We will probably keep *testing policy* since only one of the dummy variables is not significant.

Next we did a variable selection using AIC and BIC stepwise selection (see Code 1-2, Appendix 1). We can see that the only variable that is not significant is a dummy variable for *testing policy* and we cannot remove it so we leave it in.

After doing some analysis (Plot 5-6, Code 3, Appendix 1) we determined that we needed to do a transformation and this is the final model that we ended with.

$$\sqrt[3]{\text{deaths}} = \beta_0 + \beta_1 f_{\text{stay.home.restrictions}} + \beta_2 \sqrt[3]{\text{tests}} + \beta_3 f_{\text{workplace.closing}} + \beta_4 f_{\text{school.closing}} + \beta_5 f_{\text{contact.tracing}} + \beta_6 f_{\text{testing.policy}} + \beta_7 \log(\text{stringency.index})$$

After transformation we looked at the residual vs fitted and Q-Q plot again to check for linearity and check to see if there are still outliers. When we looked at the residuals vs fitted plot is still very patterned and the Q-Q plot is still heavy-tailed but less so (Plot 7, Appendix 1). We then used Cook's Distance plots (Plots 8-10, Appendix 1) and removed outliers (Code 5, Appendix 1)

After transformation and outlier/leverage points being removed we checked the summary (Table 4, Appendix 1) again and saw that *fworkplace_gathering_restrictions* was no longer significant and so we removed it and checked the linear assumptions again (Plot 11, Appendix 1). There was no difference seen. When we did a hypothesis test to see if we preferred the $H_0 : \text{mod.full6}$ or $H_1 : \text{mod.full5}$ (Code 6, Appendix 1), the p-value is 0.9087 showing us that we prefer the smaller model.

Our assumption that *confirmed* would have a strong effect on deaths was not correct. None of the data manipulation performed gave us a linear model as was seen by the clear patterning in the residuals vs. fitted plot. Because of this, we decided not to interpret this model.

Manipulating the Google mobility data into a workable data set resulted in the following predictors:

retail_and_recreation_percent_change_from_baseline,
grocery_and_pharmacy_percent_change_from_baseline, *parks_percent_change_from_baseline*,
transit_stations_percent_change_from_baseline, *workplaces_percent_change_from_baseline*, and
residential_percent_change_from_baseline. We then combined them with the full model from the base data set to create our new full model.

We ran an ANOVA comparing the full model with the null model (Table 1, Appendix 2a). The resulting p-value was $<2.2e-16$ so we reject the null model and conclude that there is at least one predictor in the full model that is significant.

Because the current model did not meet our assumptions of linearity, we decided to run a variable selection to choose a better model (Table 2, Appendix 2a). We compared eight models by looking at adjusted R-squared, CP values, and BIC values (Table 3, Appendix 2a). The model we chose had seven predictor variables. (Table 1-2, Plot 1-2, Appendix 2a)

Next, we ran transformations of all non-factor predictors. Resulting in a square root transformation for *confirmed* (Table 4, Appendix 2a). We also ran a transformation for the response variable which resulted in

a square root transformation for *deaths* (Plot 3, Appendix 2a).

Next, we checked for outliers and high leverage points. We set $|r_i| > 2$ and plotted the data to identify bad leverage points (Plot 4, Appendix 2a). A plot to check for high Cook's distance values showed none were greater than 0.5 (Plot 5, Appendix 2a). As a result, we decided not to remove any data points.

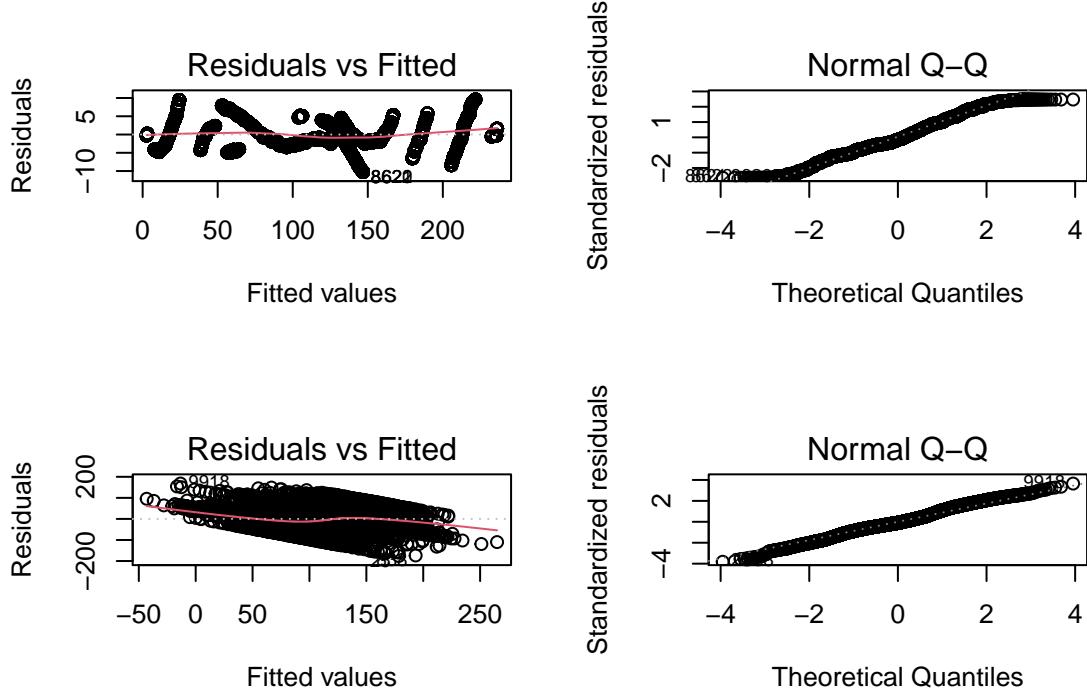
Our final model does not include any Google mobility predictors. The response is \sqrt{deaths} and the predictors are \sqrt{tests} , fschool_closing, fworkplace_closing, fstay_home_restrictions, ftesting_policy, and fcontact_tracing. Checking the final diagnostics plots, we see that the assumptions of linearity are not met (Plot 6, Appendix 2a).

For our next model, we decided to remove all base COVID-19 numerical data from the original data set. The model included categorical base COVID-19 data and Google mobility data. After exploring this model, we came to the same conclusion as the previous model, that assumptions of linearity were not met. Because of these results, we decided to remove all base COVID-19 predictors and work solely with Google mobility data.

We looked at adding a categorical variable to our model however the linear assumptions kept getting worse so we chose to leave the categorical variables out of our model and changed our questions to match this.

For the World Bank Data set, we only had one annual data point for each country. This meant that we had the same data point for every day which caused a singularity when we tried to analyze the data and combine it with the original COVID data set. We also did not have state data which is what we wanted to analyze. At the end, we only had the country by country data and could only look at one day and found that most of the variables were consistently lacking significant amounts of data points, which led to serious issues with the reliability of the data. Eventually we decided to only focus on the base data set and combine it with the Google Mobility tracking data.

Diagnostic Checks:



The top two plots are the model using categorical variables and the bottom two plots are the numerical data only. There is a stark difference between the two. The second model is definitely satisfies the linearity assumptions.

Interpretation:

$$\begin{aligned}\sqrt{\text{deaths}} = & 0.2876 + 347.5425 \text{retail and recreation percent change from baseline}^2 - \\& 536.4473\sqrt{\text{grocery and pharmacy percent change from baseline}} - \\& 15.9176\log(\text{parks percent change from baseline}) - \\& 44.9572\log(\text{transit stations percent change from baseline}) - \\& 55.1082\text{workplaces percent change from baseline} + 392.1944\text{residential percent change from baseline})^{-2}\end{aligned}$$

We come to the conclusion that this model explains 43.11% of the variability seen in the number of California Covid deaths, a one unit increase in people going to areas of *retail and recreation*² with the other predictors held fixed is associated with an increase in $\sqrt{\text{deaths}}$ by 347.54, a one unit increase in people going to areas of *grocery and pharmacy* with the other predictors held fixed is associated with an increase in $\sqrt{\text{deaths}}$ by -536.45, a one unit increase in people going to areas of $\log(\text{parks})$ with the other predictors held fixed is associated with an increase in $\sqrt{\text{deaths}}$ by -15.92, a one unit increase in people going to areas of $\log(\text{transit stations})$ with the other predictors held fixed is associated with an increase in $\sqrt{\text{deaths}}$ by -44.96, a one unit increase in people going to areas of workplaces with the other predictors held fixed is associated with an increase in $\sqrt{\text{deaths}}$ by -55.11, and a one unit increase in people going to areas of *residential*⁻² with the other predictors held fixed is associated with an increase in $\sqrt{\text{deaths}}$ by 392.19.

Conclusions

For the first question, a linear regression model using only variables from the base data set did not meet the required assumptions of normality and thus we were unable to answer this question..

For the second question, a linear regression model using variables from base data and Google mobility data did not meet the required assumptions of normality when we included any categorical variables as predictors. So we created a linear regression model using only numerical variables from the Google mobility data, this came the closest to meeting assumptions of normality. From this we found that the Retail and Recreation variable as well as the Residential Variable are positively correlated with deaths and the Grocery and Pharmacy, Parks, Workplaces and Transit Station are negatively correlated with deaths.

For the third question, we were unable to find a usable data set and thus were unable to answer this question.

Appendices

Appendix 1: R Code for Original COVID-19 Data Set

Code 1: The AIC model kept fstay_home_restrictions, tests, fworkplace_closing, fschool_closing, fcontact_tracing, ftesting_policy, and stringency_index as the predictors in the ideal model. data

```
##  
## Call:  
## lm(formula = deaths ~ fstay_home_restrictions + tests + fworkplace_closing +  
##      fschool_closing + fcontact_tracing + ftesting_policy + stringency_index,  
##      data = fbase_data)  
##  
## Coefficients:  
##              (Intercept)  fstay_home_restrictions2          tests  
##                  -6.026e+03           -6.378e+03        1.133e-03  
##      fworkplace_closing2      fworkplace_closing3  fschool_closing3  
##                  5.127e+03            8.405e+03       -5.347e+03  
##      fcontact_tracing2     ftesting_policy2  ftesting_policy3  
##                  -1.676e+03           9.524e+02       -2.803e+01  
##      stringency_index  
##                  1.162e+02
```

Code 2: The BIC is the same as the AIC, we chose to use BIC.

```
##  
## Call:  
## lm(formula = deaths ~ fstay_home_restrictions + tests + fworkplace_closing +  
##      fschool_closing + fcontact_tracing + ftesting_policy + stringency_index,  
##      data = fbase_data)  
##  
## Coefficients:  
##              (Intercept)  fstay_home_restrictions2          tests  
##                  -6.026e+03           -6.378e+03        1.133e-03  
##      fworkplace_closing2      fworkplace_closing3  fschool_closing3  
##                  5.127e+03            8.405e+03       -5.347e+03  
##      fcontact_tracing2     ftesting_policy2  ftesting_policy3  
##                  -1.676e+03           9.524e+02       -2.803e+01  
##      stringency_index  
##                  1.162e+02
```

Code 3: The powerTransformation suggests we use a cube root transformation on *tests* and a logarithmic transformation on *stringency_index*.

```
## bcPower Transformations to Multinormality  
##          Est Power Rounded Pwr Wald Lwr Bnd Wald Upr Bnd  
## tests         0.2715      0.27    0.2178    0.3252  
## stringency_index -0.4417      0.00   -1.0026    0.1193  
##  
## Likelihood ratio test that transformation parameters are equal to 0  
## (all log transformations)  
##          LRT df      pval
```

```

## LR test, lambda = (0 0) 135.8532 2 < 2.22e-16
##
## Likelihood ratio test that no transformations are needed
##          LRT df      pval
## LR test, lambda = (1 1) 420.7194 2 < 2.22e-16

```

Code 4: There are two leverage points and 3 outliers.

```

## 1 2
## 1 2

## 33 34 35
## 33 34 35

##   1   2   3   4   5   6   7   8   9   10  11  29  30  31  32  33  34  35 352 353
##   1   2   3   4   5   6   7   8   9   10  11  29  30  31  32  33  34  35 352 353
## 354 355
## 354 355

```

Code 5: Remove all leverage and outliers from fbase_data.

Code 6:

```

## Analysis of Variance Table
##
## Model 1: (deaths~{
##   1/3
## }) ~ fstay_home_restrictions + I(tests~{
##   1/3
## }) + fschool_closing + fcontact_tracing + ftesting_policy + log(stringency_index)
## Model 2: (deaths~{
##   1/3
## }) ~ fstay_home_restrictions + I(tests~{
##   1/3
## }) + fworkplace_closing + fschool_closing + fcontact_tracing +
##       ftesting_policy + log(stringency_index)
##   Res.Df   RSS Df Sum of Sq    F Pr(>F)
## 1     352 103.02
## 2     351 103.02  1  0.0038684 0.0132 0.9087

```

Table 1: $H_0 : \beta_1 = \beta_2 = \dots = \beta_9 = 0$
 $H_1 : \text{At least one } \beta_i \neq 0 \text{ for } i = 1, 2, \dots, 9$

```

## Analysis of Variance Table
##
## Model 1: deaths ~ 1
## Model 2: deaths ~ confirmed + tests + fschool_closing + fworkplace_closing +
##           fgatherings_restrictions + fstay_home_restrictions + ftesting_policy +
##           fcontact_tracing + stringency_index
##   Res.Df   RSS Df Sum of Sq    F Pr(>F)

```

```

## 1     364 8.1640e+10
## 2     352 4.7587e+08 12 8.1164e+10 5003.1 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Table 2: This summary table shows us that confirmed and gathering restrictions will probably be removed. We may keep testing policy since only one of the dummy variables is not significant.

```

##
## Call:
## lm(formula = deaths ~ confirmed + tests + fschool_closing + fworkplace_closing +
##      fgatherings_restrictions + fstay_home_restrictions + ftesting_policy +
##      fcontact_tracing + stringency_index, data = fbase_data)
##
## Residuals:
##    Min      1Q  Median      3Q      Max
## -3917.7  -536.0  -114.1   506.1  4360.5
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)              -6.059e+03  3.202e+03  -1.892  0.05927 .
## confirmed                -3.993e-04  9.071e-04  -0.440  0.66009
## tests                     1.169e-03  8.586e-05  13.614 < 2e-16 ***
## fschool_closing3          -5.411e+03  5.241e+02 -10.325 < 2e-16 ***
## fworkplace_closing2        6.002e+03  1.330e+03   4.511 8.79e-06 ***
## fworkplace_closing3        9.029e+03  1.649e+03   5.476 8.29e-08 ***
## fgatherings_restrictions3 -2.429e+03  1.921e+03  -1.265  0.20685
## fgatherings_restrictions4 -2.317e+03  2.002e+03  -1.157  0.24806
## fstay_home_restrictions2  -6.471e+03  2.440e+02 -26.518 < 2e-16 ***
## ftesting_policy2           9.374e+02  3.378e+02   2.775  0.00582 **
## ftesting_policy3           1.705e+01  4.664e+02   0.037  0.97085
## fcontact_tracing2         -1.732e+03  3.069e+02  -5.643 3.44e-08 ***
## stringency_index            1.391e+02  6.855e+01   2.030  0.04314 *
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1163 on 352 degrees of freedom
## Multiple R-squared:  0.9942, Adjusted R-squared:  0.994
## F-statistic:  5003 on 12 and 352 DF,  p-value: < 2.2e-16

```

Table 3: This is a summary of the model found after BIC Stepwise Selection.

```

##
## Call:
## lm(formula = deaths ~ fstay_home_restrictions + tests + fworkplace_closing +
##      fschool_closing + fcontact_tracing + ftesting_policy + stringency_index,
##      data = fbase_data)
##
## Residuals:
##    Min      1Q  Median      3Q      Max
## -3925.3  -548.4  -118.5   559.9  4361.3
## 

```

```

## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)           -6.026e+03  1.972e+03 -3.056 0.002410 **
## fstay_home_restrictions2 -6.378e+03  2.051e+02 -31.101 < 2e-16 ***
## tests                  1.133e-03  1.147e-05  98.840 < 2e-16 ***
## fworkplace_closing2     5.127e+03  1.092e+03   4.695 3.82e-06 ***
## fworkplace_closing3     8.405e+03  1.217e+03   6.905 2.33e-11 ***
## fschool_closing3       -5.347e+03  4.619e+02 -11.576 < 2e-16 ***
## fcontact_tracing2      -1.676e+03  2.356e+02 -7.112 6.34e-12 ***
## ftesting_policy2        9.524e+02  3.350e+02   2.843 0.004723 **
## ftesting_policy3       -2.803e+01  4.298e+02 -0.065 0.948043
## stringency_index        1.162e+02  3.457e+01   3.360 0.000863 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1161 on 355 degrees of freedom
## Multiple R-squared:  0.9941, Adjusted R-squared:  0.994
## F-statistic:  6691 on 9 and 355 DF,  p-value: < 2.2e-16

```

Table 4:

```

##
## Call:
## lm(formula = (deaths~{
##   1/3
## }) ~ fstay_home_restrictions + I(tests~{
##   1/3
## }) + fworkplace_closing + fschool_closing + fcontact_tracing +
##   ftesting_policy + log(stringency_index), data = fbase_data1)
##
## Residuals:
##      Min      1Q      Median      3Q      Max 
## -1.23640 -0.31719 -0.04829  0.21613  1.90884
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)           -21.143270  4.685643 -4.512 8.76e-06 ***
## fstay_home_restrictions2 -1.875099  0.095475 -19.640 < 2e-16 ***
## I(tests~{\n   1/3\n})      0.089391  0.000846 105.659 < 2e-16 ***
## fworkplace_closing3     -0.030021  0.261497 -0.115  0.909
## fschool_closing3        -2.000958  0.217052 -9.219 < 2e-16 ***
## fcontact_tracing2      -1.612712  0.092226 -17.487 < 2e-16 ***
## ftesting_policy2         3.274730  0.162020 20.212 < 2e-16 ***
## ftesting_policy3         3.402234  0.216109 15.743 < 2e-16 ***
## log(stringency_index)    6.000421  1.126961   5.324 1.81e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5418 on 351 degrees of freedom
## Multiple R-squared:  0.996, Adjusted R-squared:  0.996
## F-statistic: 1.106e+04 on 8 and 351 DF,  p-value: < 2.2e-16

```

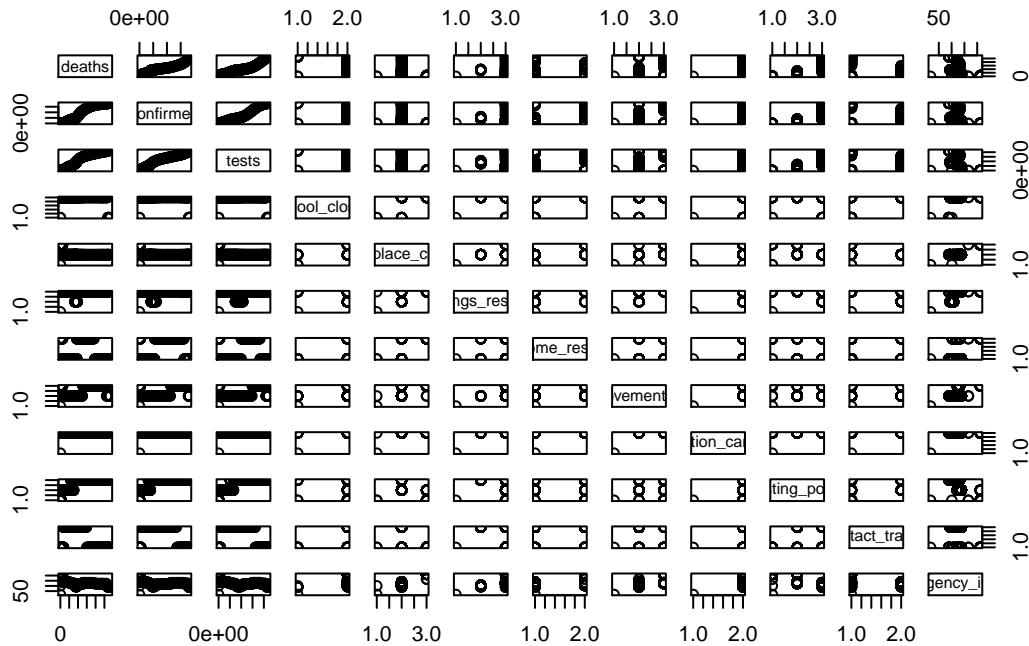
Table 5: This is our final model.

```

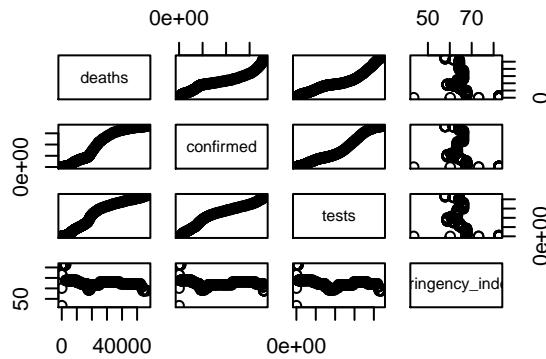
## 
## Call:
## lm(formula = (deaths~{
##   1/3
## }) ~ fstay_home_restrictions + I(tests~{
##   1/3
## }) + fschool_closing + fcontact_tracing + ftesting_policy + log(stringency_index),
##   data = fbase_data1)
##
## Residuals:
##      Min        1Q     Median        3Q       Max
## -1.23530 -0.31336 -0.04861  0.21695  1.90872
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)              -2.085e+01  3.928e+00 -5.308 1.97e-07 ***
## fstay_home_restrictions2 -1.877e+00  9.370e-02 -20.034 < 2e-16 ***
## I(tests~{\n  1/3\n})      8.943e-02  7.853e-04 113.871 < 2e-16 ***
## fschool_closing3         -1.992e+00  2.034e-01 -9.796 < 2e-16 ***
## fcontact_tracing2        -1.611e+00  9.136e-02 -17.638 < 2e-16 ***
## ftesting_policy2          3.281e+00  1.527e-01 21.481 < 2e-16 ***
## ftesting_policy3          3.402e+00  2.158e-01 15.765 < 2e-16 ***
## log(stringency_index)    5.925e+00  9.165e-01  6.465 3.38e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.541 on 352 degrees of freedom
## Multiple R-squared:  0.996, Adjusted R-squared:  0.996
## F-statistic: 1.267e+04 on 7 and 352 DF, p-value: < 2.2e-16

```

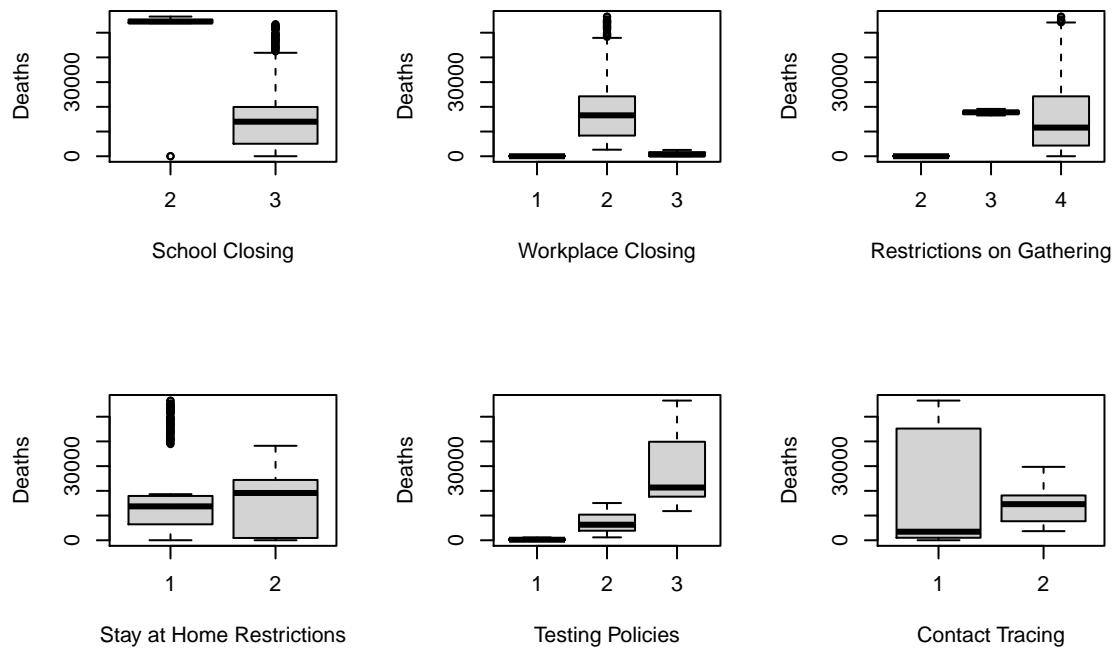
Plot 1: Each of these are really small and it is hard to derive anything useful from them.



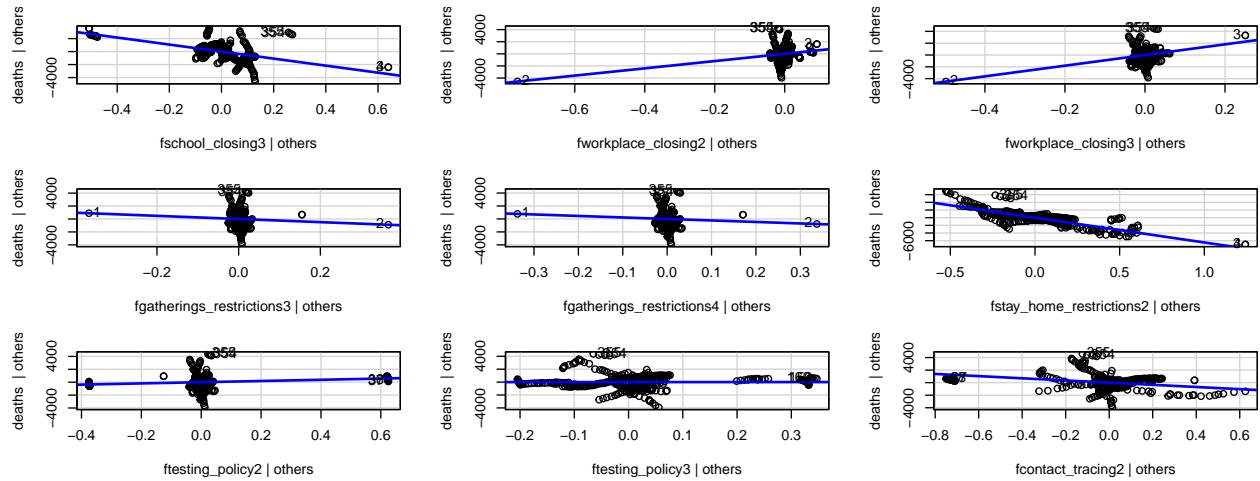
Plot 2: Scatterplots of the numerical variables in the original data set.

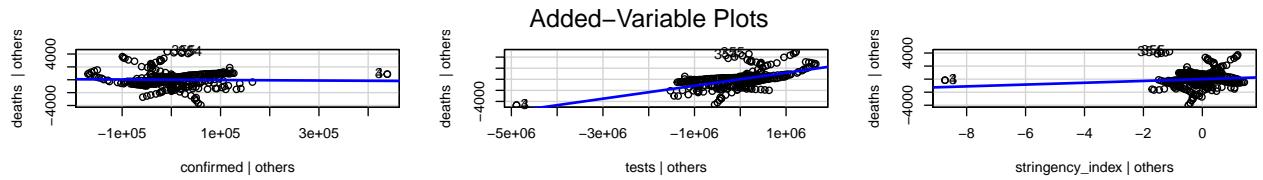


Plot 3: Box plots of the categorical variables in the original data set.

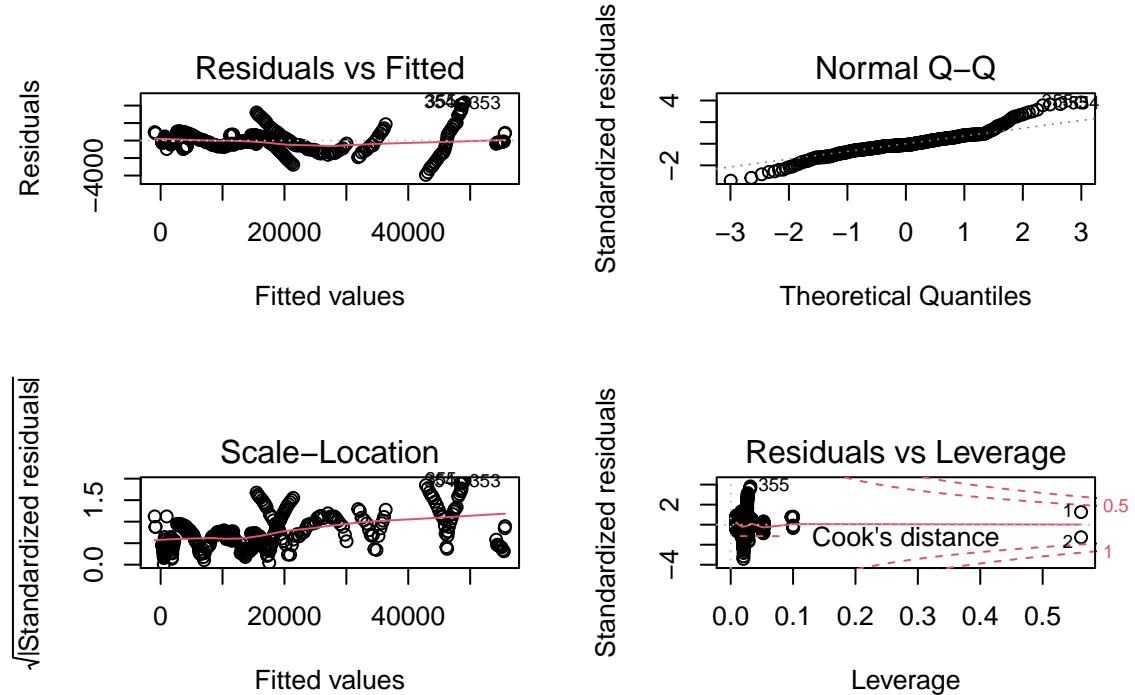


Plot 4: Added variable plots for both the categorical variables.

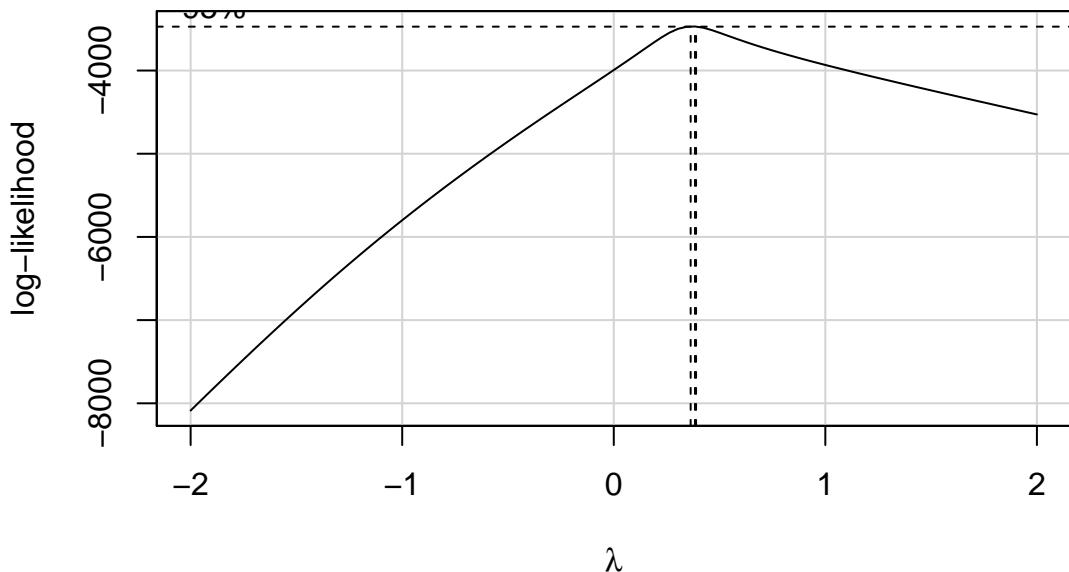




Plot 5: Checking normality prior to transformation

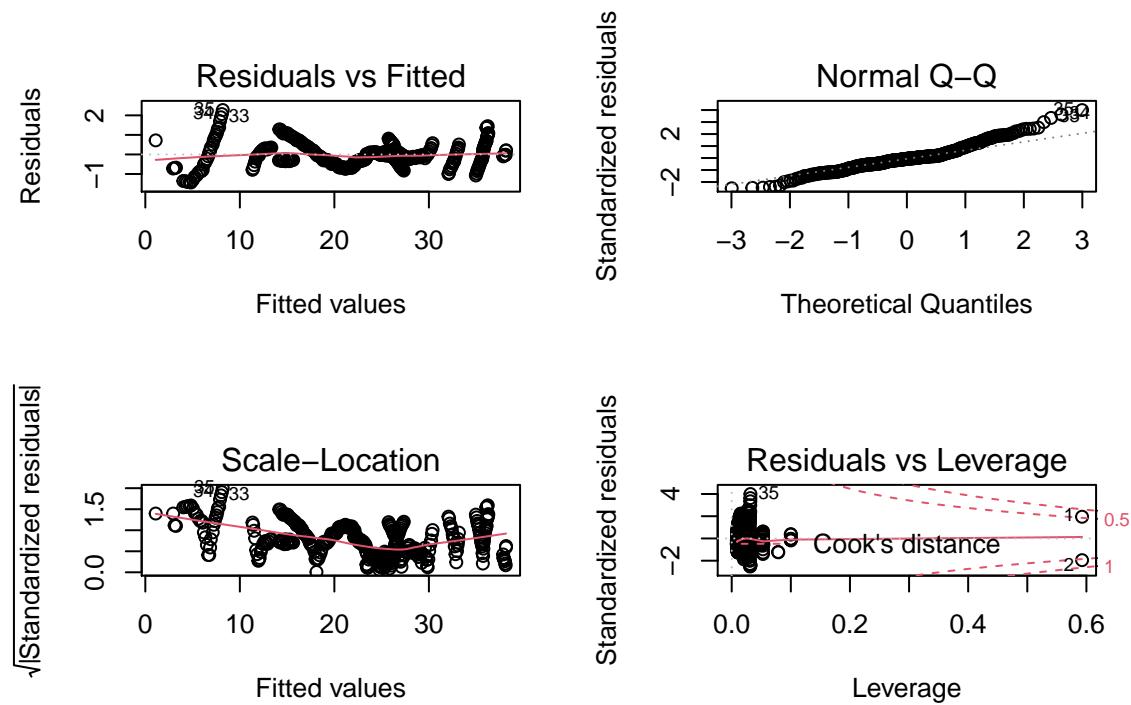


Plot 6: According to boxCox we should do a cube root transformation on the response *deaths*.

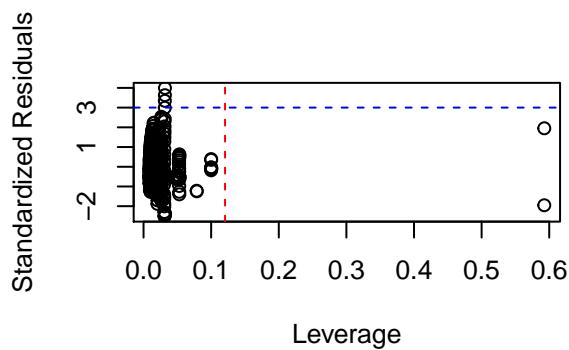


```
## [1] 0.3838384
```

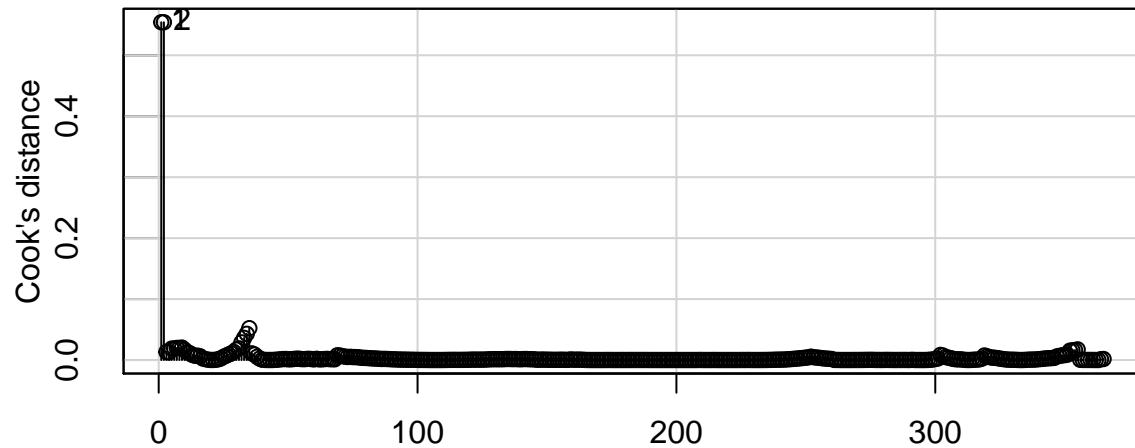
Plot 7: Post transformation linearity check. The residuals vs fitted plot is still very patterned and the Q-Q plot is still heavy-tailed but less so.



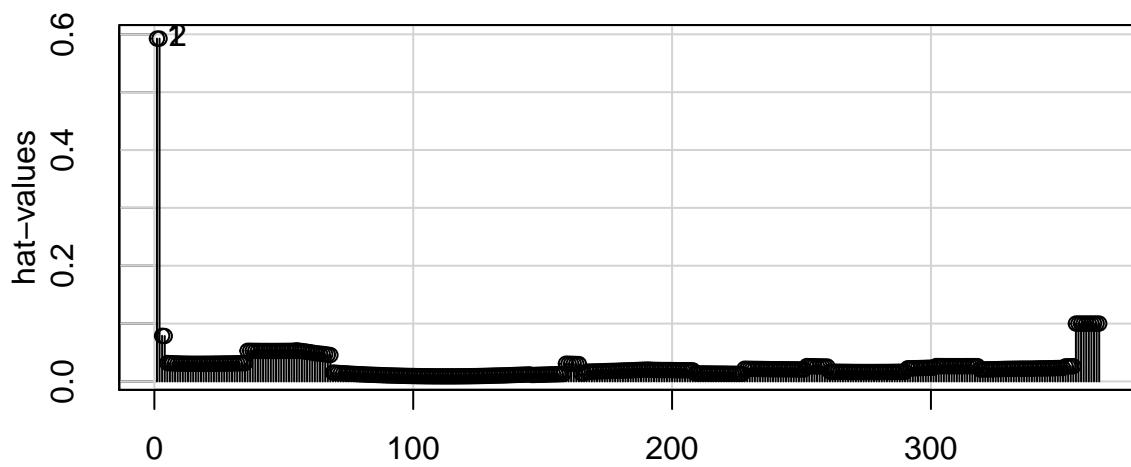
Plot 8: From the Cook's InfuleceIndexPlot and hat-values influenceIndexPlot we can see that we should definitely look at points 1 and 2.



Diagnostic Plots

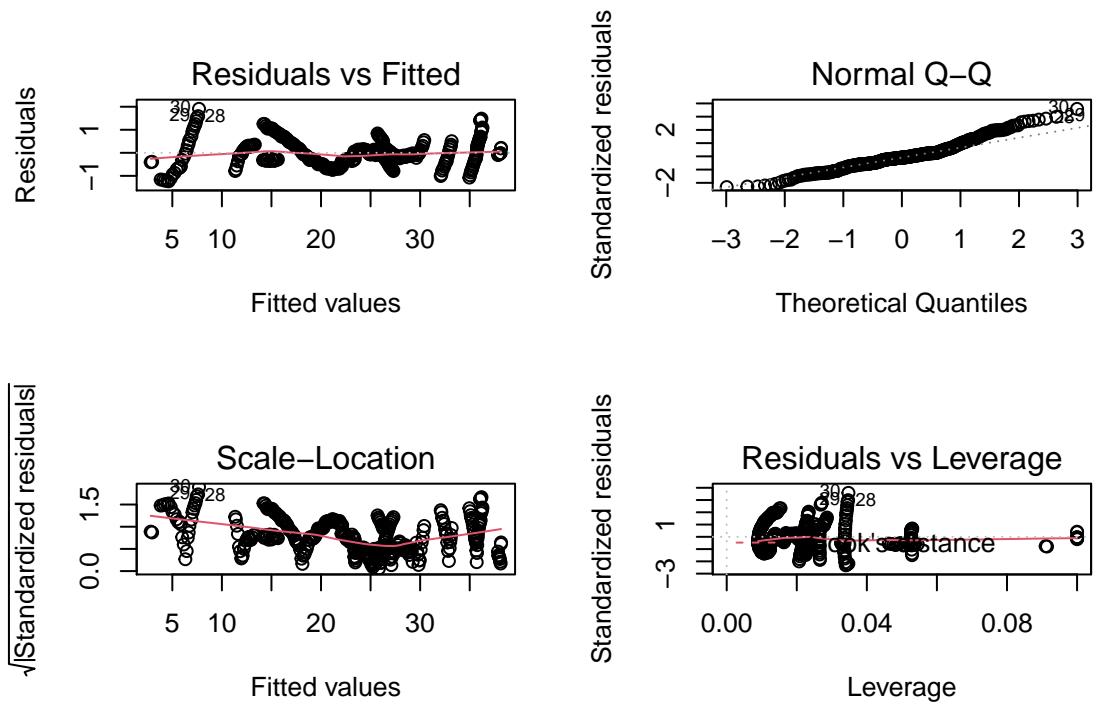


Index Diagnostic Plots

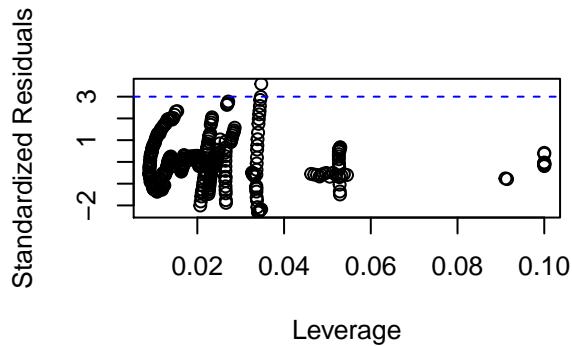


Index

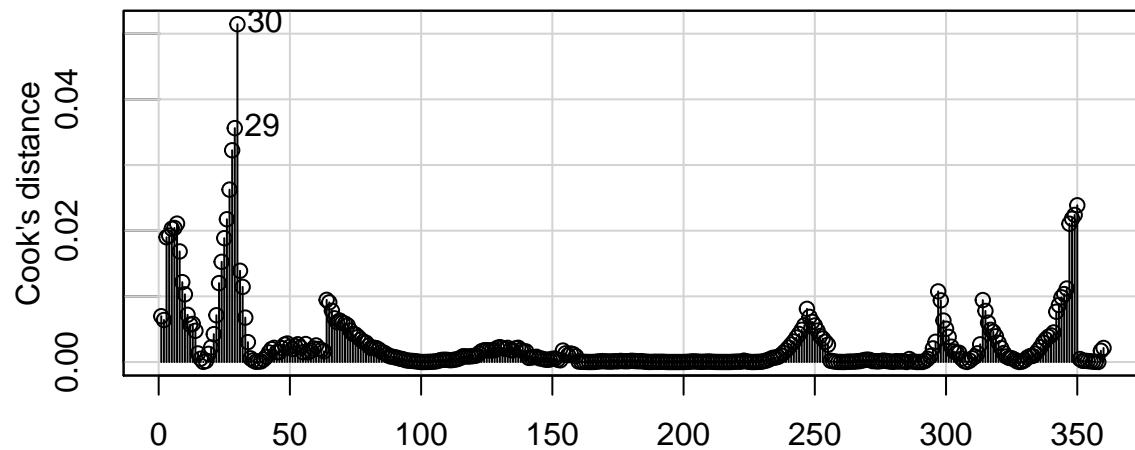
Plot 9: Checking the linearity after the removal of rows 1, 2, 33, 34, and 35. Looks a little better.



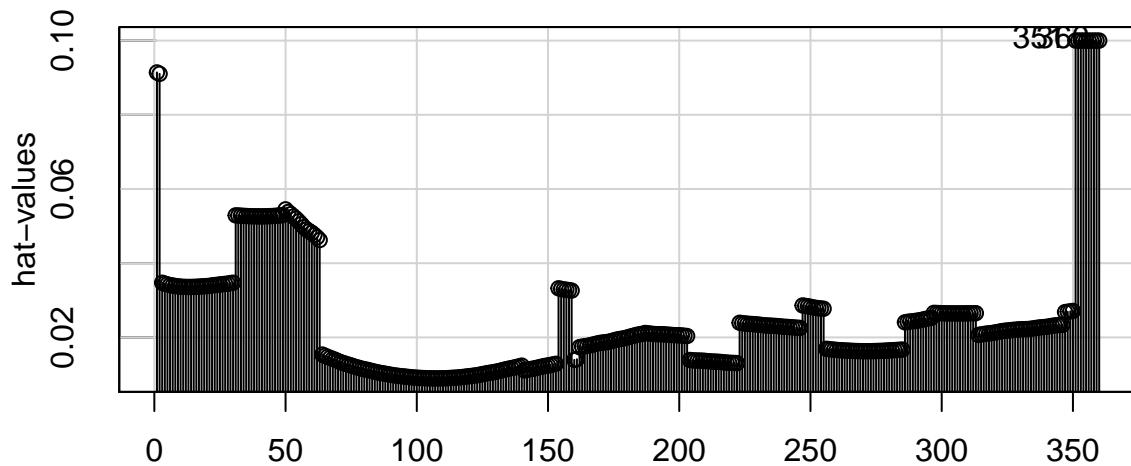
Plot 10: Checking Cook's plot again after the removal of rows 1, 2, 33, 34, and 35. Looks better.



Diagnostic Plots

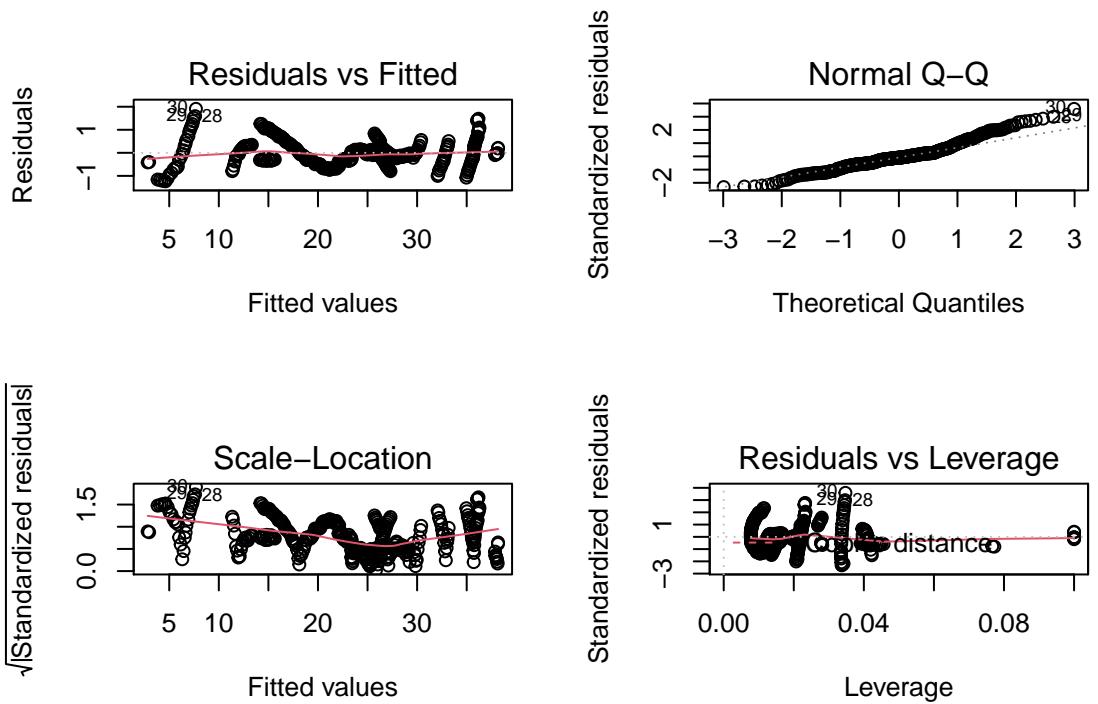


Index Diagnostic Plots



Index

Plot 11: After removing the outliers work_place_restrictions is no longer significant so we removed it and the plots look roughly the same so we remove it from our model.



Appendix 2a: R Code for Google Mobility + Categorical Variables

Code 1:

Table 1:

```
## Analysis of Variance Table
##
## Model 1: deaths ~ 1
## Model 2: deaths ~ retail_and_recreation_percent_change_from_baseline +
##           grocery_and_pharmacy_percent_change_from_baseline + parks_percent_change_from_baseline +
##           transit_stations_percent_change_from_baseline + workplaces_percent_change_from_baseline +
##           residential_percent_change_from_baseline + date + confirmed +
##           tests + fschool_closing + fworkplace_closing + fgatherings_restrictions +
##           fstay_home_restrictions + ftesting_policy + fcontact_tracing +
##           stringency_index
##   Res.Df      RSS Df  Sum of Sq      F    Pr(>F)
## 1 12972 3.0456e+12
## 2 12953 1.6726e+10 19 3.0288e+12 123455 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Table 2:

```
## Subset selection object
## Call: regsubsets.formula(deaths ~ retail_and_recreation_percent_change_from_baseline +
##           grocery_and_pharmacy_percent_change_from_baseline + parks_percent_change_from_baseline +
##           transit_stations_percent_change_from_baseline + workplaces_percent_change_from_baseline +
##           residential_percent_change_from_baseline + date + confirmed +
##           tests + fschool_closing + fworkplace_closing + fgatherings_restrictions +
##           fstay_home_restrictions + ftesting_policy + fcontact_tracing +
##           stringency_index, data = cacovid_mobility)
## 19 Variables  (and intercept)
##                                     Forced in    Forced out
## retail_and_recreation_percent_change_from_baseline FALSE FALSE
## grocery_and_pharmacy_percent_change_from_baseline FALSE FALSE
## parks_percent_change_from_baseline FALSE FALSE
## transit_stations_percent_change_from_baseline FALSE FALSE
## workplaces_percent_change_from_baseline FALSE FALSE
## residential_percent_change_from_baseline FALSE FALSE
## date FALSE FALSE
## confirmed FALSE FALSE
## tests FALSE FALSE
## fschool_closing3 FALSE FALSE
## fworkplace_closing2 FALSE FALSE
## fworkplace_closing3 FALSE FALSE
## fgatherings_restrictions3 FALSE FALSE
## fgatherings_restrictions4 FALSE FALSE
## fstay_home_restrictions2 FALSE FALSE
## ftesting_policy2 FALSE FALSE
## ftesting_policy3 FALSE FALSE
## fcontact_tracing2 FALSE FALSE
## stringency_index FALSE FALSE
```

```

## 1 subsets of each size up to 8
## Selection Algorithm: exhaustive
##           retail_and_recreation_percent_change_from_baseline
## 1  ( 1 ) " "
## 2  ( 1 ) " "
## 3  ( 1 ) " "
## 4  ( 1 ) " "
## 5  ( 1 ) " "
## 6  ( 1 ) " "
## 7  ( 1 ) " "
## 8  ( 1 ) " "
##           grocery_and_pharmacy_percent_change_from_baseline
## 1  ( 1 ) " "
## 2  ( 1 ) " "
## 3  ( 1 ) " "
## 4  ( 1 ) " "
## 5  ( 1 ) " "
## 6  ( 1 ) " "
## 7  ( 1 ) " "
## 8  ( 1 ) " "
##           parks_percent_change_from_baseline
## 1  ( 1 ) " "
## 2  ( 1 ) " "
## 3  ( 1 ) " "
## 4  ( 1 ) " "
## 5  ( 1 ) " "
## 6  ( 1 ) " "
## 7  ( 1 ) " "
## 8  ( 1 ) " "
##           transit_stations_percent_change_from_baseline
## 1  ( 1 ) " "
## 2  ( 1 ) " "
## 3  ( 1 ) " "
## 4  ( 1 ) " "
## 5  ( 1 ) " "
## 6  ( 1 ) " "
## 7  ( 1 ) " "
## 8  ( 1 ) " "
##           workplaces_percent_change_from_baseline
## 1  ( 1 ) " "
## 2  ( 1 ) " "
## 3  ( 1 ) " "
## 4  ( 1 ) " "
## 5  ( 1 ) " "
## 6  ( 1 ) " "
## 7  ( 1 ) " "
## 8  ( 1 ) " "
##           residential_percent_change_from_baseline date confirmed tests
## 1  ( 1 ) " "          " "   "*"   " "
## 2  ( 1 ) " "          " "   "*"   " "
## 3  ( 1 ) " "          " "   " "   "*" 
## 4  ( 1 ) " "          " "   " "   "*" 
## 5  ( 1 ) " "          " "   " "   "*" 
## 6  ( 1 ) " "          " "   " "   "*"

```

```

## 7 ( 1 ) " " " " "*"
## 8 ( 1 ) " " "*" " *"
##           fschool_closing3 fworkplace_closing2 fworkplace_closing3
## 1 ( 1 ) " " " "
## 2 ( 1 ) " " " "
## 3 ( 1 ) " " " "
## 4 ( 1 ) "*" " "
## 5 ( 1 ) "*" " "
## 6 ( 1 ) "*" " "
## 7 ( 1 ) "*" " "
## 8 ( 1 ) "*" " "
##           fgatherings_restrictions3 fgatherings_restrictions4
## 1 ( 1 ) " " " "
## 2 ( 1 ) " " " "
## 3 ( 1 ) " " " "
## 4 ( 1 ) " " " "
## 5 ( 1 ) " " " "
## 6 ( 1 ) " " " "
## 7 ( 1 ) " " " "
## 8 ( 1 ) " " " "
##           fstay_home_restrictions2 ftesting_policy2 ftesting_policy3
## 1 ( 1 ) " " " "
## 2 ( 1 ) "*" " "
## 3 ( 1 ) "*" " "
## 4 ( 1 ) "*" " "
## 5 ( 1 ) "*" " "
## 6 ( 1 ) "*" " "
## 7 ( 1 ) "*" " "
## 8 ( 1 ) "*" " "
##           fcontact_tracing2 stringency_index
## 1 ( 1 ) " " " "
## 2 ( 1 ) " " " "
## 3 ( 1 ) " " " "
## 4 ( 1 ) " " "*" "
## 5 ( 1 ) "*" " "
## 6 ( 1 ) "*" " "
## 7 ( 1 ) "*" " "
## 8 ( 1 ) "*" " "

```

Table 3:

	subset.summary.adjr2	subset.summary.cp	subset.summary.bic
## 1	0.9605253	80128.9929	-41912.02
## 2	0.9780352	38831.2128	-49508.58
## 3	0.9881143	15062.2614	-57466.84
## 4	0.9922731	5256.1681	-63044.89
## 5	0.9930667	3385.6083	-64442.39
## 6	0.9933658	2681.1650	-65006.04
## 7	0.9939441	1318.7697	-66180.73
## 8	0.9941868	747.6231	-66702.84

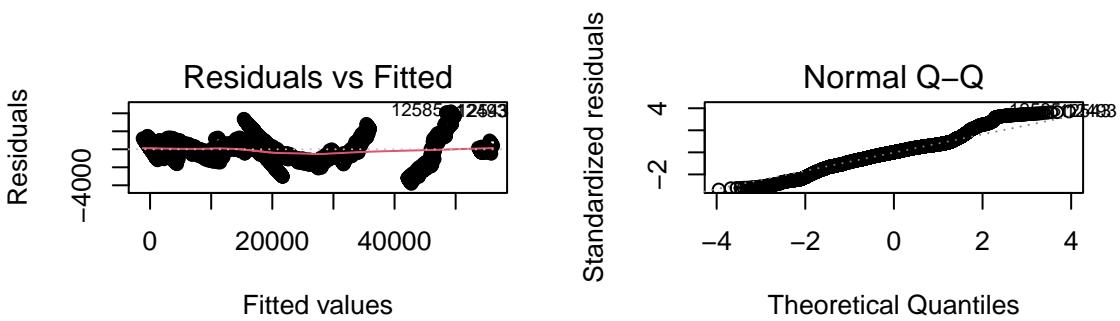
Table 4:

```

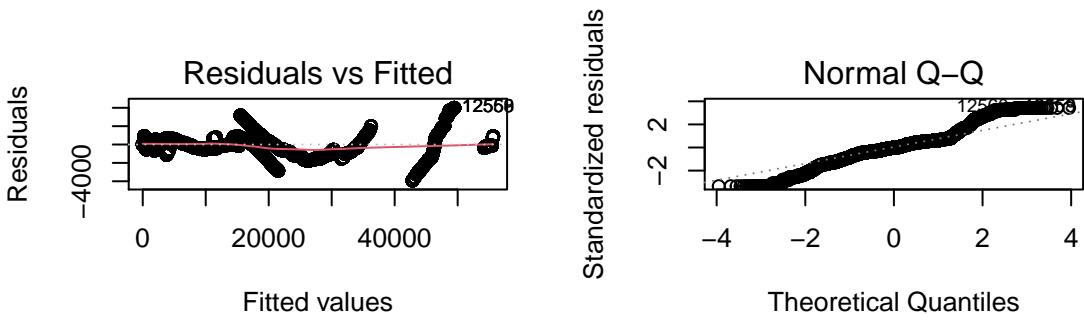
## bcPower Transformation to Normality
##   Est Power Rounded Pwr Wald Lwr Bnd Wald Upr Bnd
## Y1    0.3642      0.36     0.3529      0.3754
##
## Likelihood ratio test that transformation parameter is equal to 0
## (log transformation)
##          LRT df      pval
## LR test, lambda = (0) 5177.776 1 < 2.22e-16
##
## Likelihood ratio test that no transformation is needed
##          LRT df      pval
## LR test, lambda = (1) 8574.034 1 < 2.22e-16

```

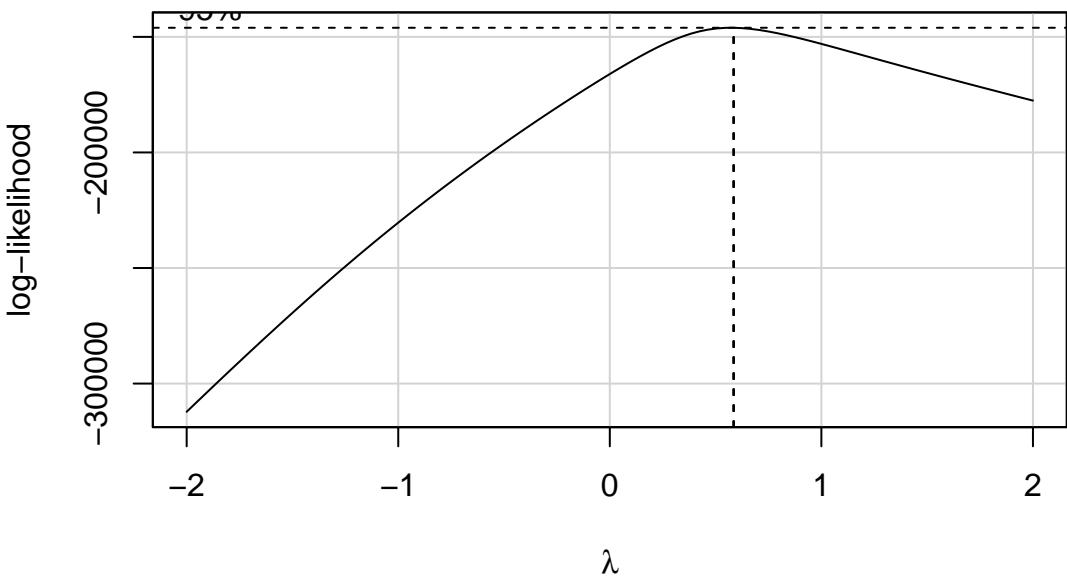
Plot 1:

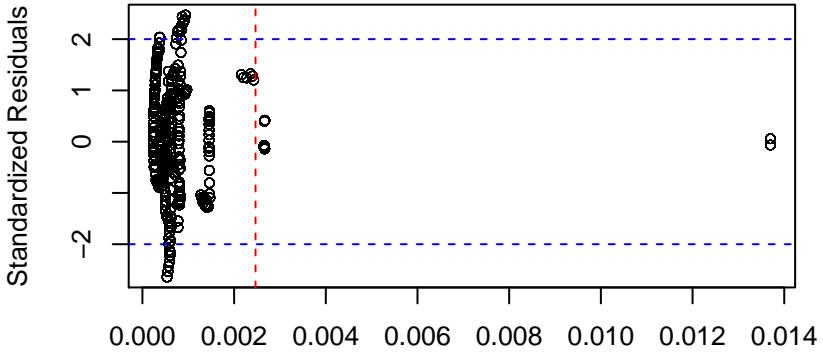


Plot 2:



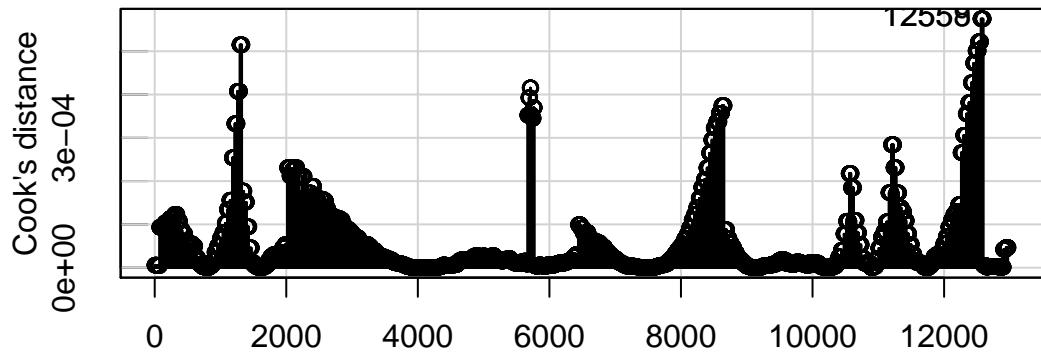
Plot 3:



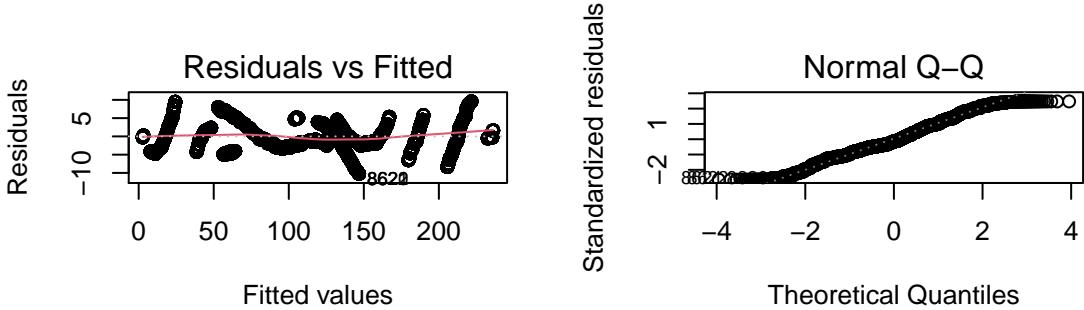


Plot 4: Leverage

Diagnostic Plots



Plot 5: Index



Plot 6: Fitted values

Appendix 2b: R Code for Google Mobility Only

Table 1:

```

## 
## Call:
## lm(formula = deaths ~ retail_and_recreation_percent_change_from_baseline +
##      grocery_and_pharmacy_percent_change_from_baseline + parks_percent_change_from_baseline +
##      transit_stations_percent_change_from_baseline + workplaces_percent_change_from_baseline +
##      residential_percent_change_from_baseline, data = cacovid_mobility)
## 
## Residuals:
##    Min     1Q Median     3Q    Max 
## -28185 -8374 -3152  5292 44220 
## 
## Coefficients:
##                               Estimate Std. Error t value
## (Intercept)                73831.6   6714.1 10.997
## retail_and_recreation_percent_change_from_baseline 78601.3   1302.4 60.352
## grocery_and_pharmacy_percent_change_from_baseline -70671.7   1483.6 -47.636
## parks_percent_change_from_baseline                 -6796.8   337.1 -20.163
## transit_stations_percent_change_from_baseline     -11553.1   576.5 -20.040
## workplaces_percent_change_from_baseline          -1849.6   1847.5 -1.001
## residential_percent_change_from_baseline         -32250.9   5220.5 -6.178
## 
## Pr(>|t|) 
## (Intercept) < 2e-16 ***
## retail_and_recreation_percent_change_from_baseline < 2e-16 ***
## grocery_and_pharmacy_percent_change_from_baseline < 2e-16 ***
## parks_percent_change_from_baseline                 < 2e-16 ***
## transit_stations_percent_change_from_baseline     < 2e-16 ***
## workplaces_percent_change_from_baseline           0.317
## residential_percent_change_from_baseline          6.7e-10 ***
## 
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 12420 on 12966 degrees of freedom
## Multiple R-squared:  0.3436, Adjusted R-squared:  0.3433
## F-statistic:  1131 on 6 and 12966 DF,  p-value: < 2.2e-16

```

Table 2:

```

## [1] 5180.627602 843.411004 424.594512 117.099083 6.002351 7.000000
## [1] 5
## [1] 0.08109592 0.30073378 0.32198882 0.33760972 0.34328642 0.34328653
## [1] 6

```

Table 3:

```

## bcPower Transformations to Multinormality
##   Est Power Rounded Pwr Wald Lwr Bnd Wald Upr Bnd
## Y1    1.5059      1.51     1.4613     1.5505
## Y2    0.6780      0.68     0.6239     0.7320
## Y3    0.3274      0.33     0.3044     0.3503
## Y4    0.2022      0.20     0.1793     0.2250
## Y5    1.2205      1.22     1.1899     1.2511
## Y6   -2.0512     -2.00    -2.2008    -1.9015
##
## Likelihood ratio test that transformation parameters are equal to 0
## (all log transformations)
##                               LRT df      pval
## LR test, lambda = (0 0 0 0 0 0) 16049.92 6 < 2.22e-16
##
## Likelihood ratio test that no transformations are needed
##                               LRT df      pval
## LR test, lambda = (1 1 1 1 1 1) 9967.929 6 < 2.22e-16

## Subset selection object
## Call: regsubsets.formula(deaths ~ retail_and_recreation_percent_change_from_baseline +
##   grocery_and_pharmacy_percent_change_from_baseline + parks_percent_change_from_baseline +
##   transit_stations_percent_change_from_baseline + workplaces_percent_change_from_baseline +
##   residential_percent_change_from_baseline, data = cacovid_mobility)
## 6 Variables (and intercept)
##                                     Forced in Forced out
## retail_and_recreation_percent_change_from_baseline FALSE FALSE
## grocery_and_pharmacy_percent_change_from_baseline FALSE FALSE
## parks_percent_change_from_baseline FALSE FALSE
## transit_stations_percent_change_from_baseline FALSE FALSE
## workplaces_percent_change_from_baseline FALSE FALSE
## residential_percent_change_from_baseline FALSE FALSE
## 1 subsets of each size up to 6
## Selection Algorithm: exhaustive
##   retail_and_recreation_percent_change_from_baseline
## 1 ( 1 ) "*"
## 2 ( 1 ) "*"
## 3 ( 1 ) "*"
## 4 ( 1 ) "*"
## 5 ( 1 ) "*"
## 6 ( 1 ) "*"
##   grocery_and_pharmacy_percent_change_from_baseline
## 1 ( 1 ) " "
## 2 ( 1 ) "*"
## 3 ( 1 ) "*"
## 4 ( 1 ) "*"
## 5 ( 1 ) "*"
## 6 ( 1 ) "*"
##   parks_percent_change_from_baseline
## 1 ( 1 ) " "
## 2 ( 1 ) " "
## 3 ( 1 ) "*"
## 4 ( 1 ) "*"
## 5 ( 1 ) "*"
## 6 ( 1 ) "*"

```

```

##          transit_stations_percent_change_from_baseline
## 1  ( 1 ) " "
## 2  ( 1 ) " "
## 3  ( 1 ) " "
## 4  ( 1 ) "*"
## 5  ( 1 ) "*"
## 6  ( 1 ) "*"
##          workplaces_percent_change_from_baseline
## 1  ( 1 ) " "
## 2  ( 1 ) " "
## 3  ( 1 ) " "
## 4  ( 1 ) " "
## 5  ( 1 ) " "
## 6  ( 1 ) "*"
##          residential_percent_change_from_baseline
## 1  ( 1 ) " "
## 2  ( 1 ) " "
## 3  ( 1 ) " "
## 4  ( 1 ) " "
## 5  ( 1 ) "*"
## 6  ( 1 ) "*"

```

Table 4:

```

##
## Call:
## lm(formula = sqrt(deaths) ~ I(retail_and_recreation_percent_change_from_baseline^(3/2)) +
##      sqrt(grocery_and_pharmacy_percent_change_from_baseline) +
##      I(parks_percent_change_from_baseline^(1/3)) + log(transit_stations_percent_change_from_baseline)
##      workplaces_percent_change_from_baseline + I(residential_percent_change_from_baseline^(-2)),
##      data = cacovid_mobility)
##
## Residuals:
##      Min        1Q     Median        3Q       Max
## -183.433   -27.051    -3.946   27.113   178.519
##
## Coefficients:
##                               Estimate Std. Error
## (Intercept)                  299.725   10.719
## I(retail_and_recreation_percent_change_from_baseline^(3/2))  300.985   4.353
## sqrt(grocery_and_pharmacy_percent_change_from_baseline)      -506.638  10.186
## I(parks_percent_change_from_baseline^(1/3))                 -63.938   3.869
## log(transit_stations_percent_change_from_baseline)           -43.327   1.275
## workplaces_percent_change_from_baseline                      -41.849   7.071
## I(residential_percent_change_from_baseline^(-2))            188.109  11.250
##                               t value Pr(>|t|)
## (Intercept)                  27.961 < 2e-16
## I(retail_and_recreation_percent_change_from_baseline^(3/2))  69.143 < 2e-16
## sqrt(grocery_and_pharmacy_percent_change_from_baseline)      -49.739 < 2e-16
## I(parks_percent_change_from_baseline^(1/3))                 -16.524 < 2e-16
## log(transit_stations_percent_change_from_baseline)           -33.993 < 2e-16
## workplaces_percent_change_from_baseline                      -5.918 3.33e-09
## I(residential_percent_change_from_baseline^(-2))             16.721 < 2e-16

```

```

## 
## (Intercept) ***
## I(retail_and_recreation_percent_change_from_baseline^(3/2)) ***
## sqrt(grocery_and_pharmacy_percent_change_from_baseline) ***
## I(parks_percent_change_from_baseline^(1/3)) ***
## log(transit_stations_percent_change_from_baseline) ***
## workplaces_percent_change_from_baseline ***
## I(residential_percent_change_from_baseline^(-2)) ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 46.67 on 12966 degrees of freedom
## Multiple R-squared: 0.4185, Adjusted R-squared: 0.4182
## F-statistic: 1555 on 6 and 12966 DF, p-value: < 2.2e-16

```

Table 5:

```

## 
## Call:
## lm(formula = sqrt(deaths) ~ I(retail_and_recreation_percent_change_from_baseline^{3/2}) + sqrt(grocery_and_pharmacy_percent_change_from_baseline) + I(parks_percent_change_from_baseline^{1/3}) + log(transit_stations_percent_change_from_baseline) + workplaces_percent_change_from_baseline + I(residential_percent_change_from_baseline^(-2)), data = cacovid_mobilityGO)
##
## Residuals:
##      Min       1Q     Median       3Q      Max
## -183.594  -27.072   -3.883   27.049  162.524
##
## Coefficients:
## 
## (Intercept)          Estimate
## 301.356
## I(retail_and_recreation_percent_change_from_baseline^{3/2}) 301.728
## sqrt(grocery_and_pharmacy_percent_change_from_baseline)    -507.775
## I(parks_percent_change_from_baseline^{1/3})                 -63.876
## log(transit_stations_percent_change_from_baseline)         -43.319
## workplaces_percent_change_from_baseline                     -40.584
## I(residential_percent_change_from_baseline^(-2))           186.320
## 
## Std. Error
## 10.722
## I(retail_and_recreation_percent_change_from_baseline^{3/2}) 4.355
## sqrt(grocery_and_pharmacy_percent_change_from_baseline) 10.185
## I(parks_percent_change_from_baseline^{1/3})                3.867
## log(transit_stations_percent_change_from_baseline)        1.274
## workplaces_percent_change_from_baseline                   7.075
## I(residential_percent_change_from_baseline^(-2))          11.254
## 
## t value
## 28.106
## I(retail_and_recreation_percent_change_from_baseline^{3/2}) 69.281
## sqrt(grocery_and_pharmacy_percent_change_from_baseline) -49.856

```

```

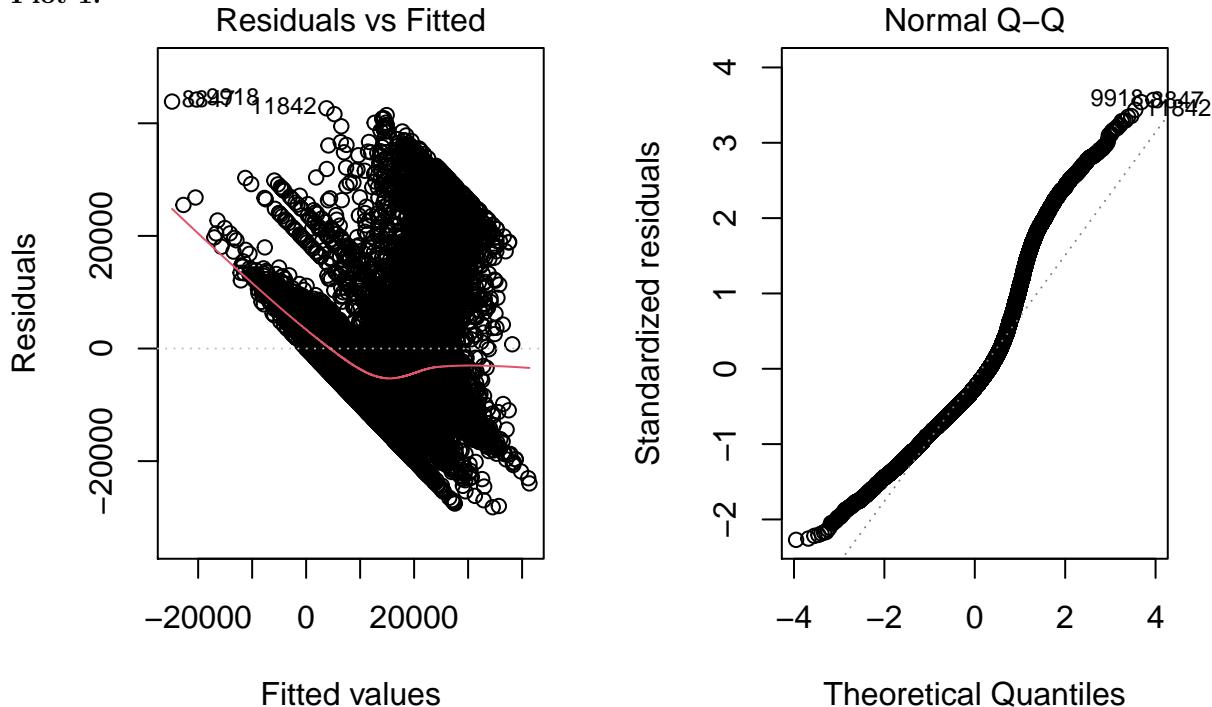
## I(parks_percent_change_from_baseline^{\n      1/3\n})           -16.516
## log(transit_stations_percent_change_from_baseline)        -34.005
## workplaces_percent_change_from_baseline                  -5.736
## I(residential_percent_change_from_baseline^(-2))       16.557
##                                         Pr(>|t|)          < 2e-16
## (Intercept)                                              < 2e-16
## I(retail_and_recreation_percent_change_from_baseline^{\n      3/2\n}) < 2e-16
## sqrt(grocery_and_pharmacy_percent_change_from_baseline) < 2e-16
## I(parks_percent_change_from_baseline^{\n      1/3\n})           < 2e-16
## log(transit_stations_percent_change_from_baseline)        < 2e-16
## workplaces_percent_change_from_baseline                 9.89e-09
## I(residential_percent_change_from_baseline^(-2))        < 2e-16
##                                         Pr(>|t|)          ***

## (Intercept)                                              ***
## I(retail_and_recreation_percent_change_from_baseline^{\n      3/2\n}) ***
## sqrt(grocery_and_pharmacy_percent_change_from_baseline) ***
## I(parks_percent_change_from_baseline^{\n      1/3\n})           ***
## log(transit_stations_percent_change_from_baseline)        ***
## workplaces_percent_change_from_baseline                  ***
## I(residential_percent_change_from_baseline^(-2))        ***

## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 46.64 on 12965 degrees of freedom
## Multiple R-squared:  0.4192, Adjusted R-squared:  0.4189
## F-statistic:  1559 on 6 and 12965 DF,  p-value: < 2.2e-16

```

Plot 1:

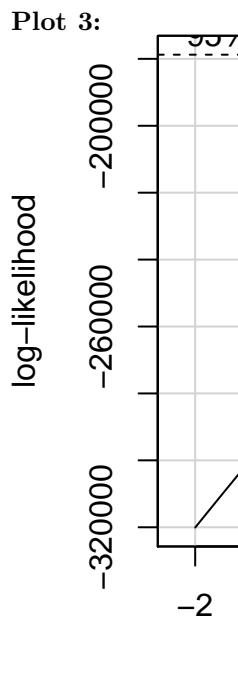
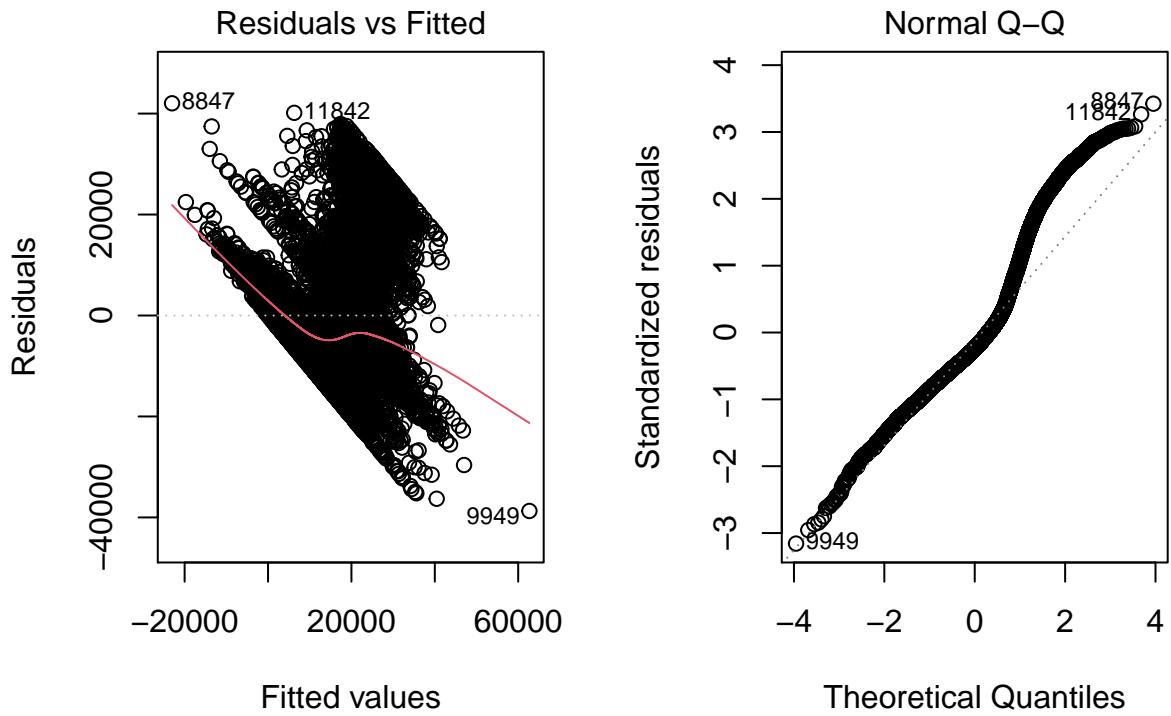


Plot 2:

```

## 
## Call:
## lm(formula = deaths ~ I(retail_and_recreation_percent_change_from_baseline^(3/2)) +
##      sqrt(grocery_and_pharmacy_percent_change_from_baseline) +
##      I(parks_percent_change_from_baseline^(1/3)) + log(transit_stations_percent_change_from_baseline)
##      workplaces_percent_change_from_baseline + I(residential_percent_change_from_baseline^(-2)),
##      data = cacovid_mobility)
##
## Residuals:
##    Min      1Q Median      3Q     Max
## -38720   -8035  -2961   4931  42039
##
## Coefficients:
##                               Estimate Std. Error
## (Intercept)                76872     2826
## I(retail_and_recreation_percent_change_from_baseline^(3/2))    71402     1148
## sqrt(grocery_and_pharmacy_percent_change_from_baseline)      -116077    2685
## I(parks_percent_change_from_baseline^(1/3))                  -20556     1020
## log(transit_stations_percent_change_from_baseline)            -9841      336
## workplaces_percent_change_from_baseline                      2237     1864
## I(residential_percent_change_from_baseline^(-2))             22854     2966
## 
## t value Pr(>|t|)
## (Intercept)          27.203 < 2e-16
## I(retail_and_recreation_percent_change_from_baseline^(3/2)) 62.220 < 2e-16
## sqrt(grocery_and_pharmacy_percent_change_from_baseline)      -43.228 < 2e-16
## I(parks_percent_change_from_baseline^(1/3))                 -20.152 < 2e-16
## log(transit_stations_percent_change_from_baseline)           -29.289 < 2e-16
## workplaces_percent_change_from_baseline                     1.200     0.23
## I(residential_percent_change_from_baseline^(-2))            7.706 1.39e-14
## 
## (Intercept)               ***
## I(retail_and_recreation_percent_change_from_baseline^(3/2)) ***
## sqrt(grocery_and_pharmacy_percent_change_from_baseline) ***
## I(parks_percent_change_from_baseline^(1/3))                 ***
## log(transit_stations_percent_change_from_baseline)           ***
## workplaces_percent_change_from_baseline
## I(residential_percent_change_from_baseline^(-2))            ***
## --- 
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 12300 on 12966 degrees of freedom
## Multiple R-squared:  0.3556, Adjusted R-squared:  0.3553
## F-statistic:  1193 on 6 and 12966 DF,  p-value: < 2.2e-16

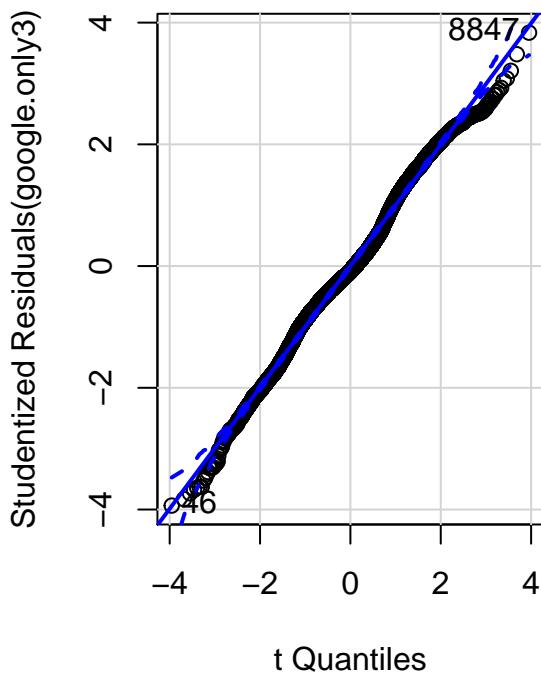
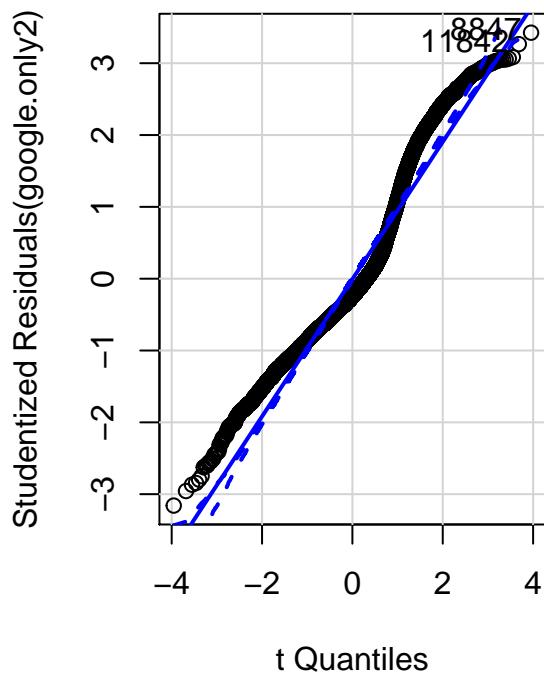
```



```
## [1] 0.3838384
```

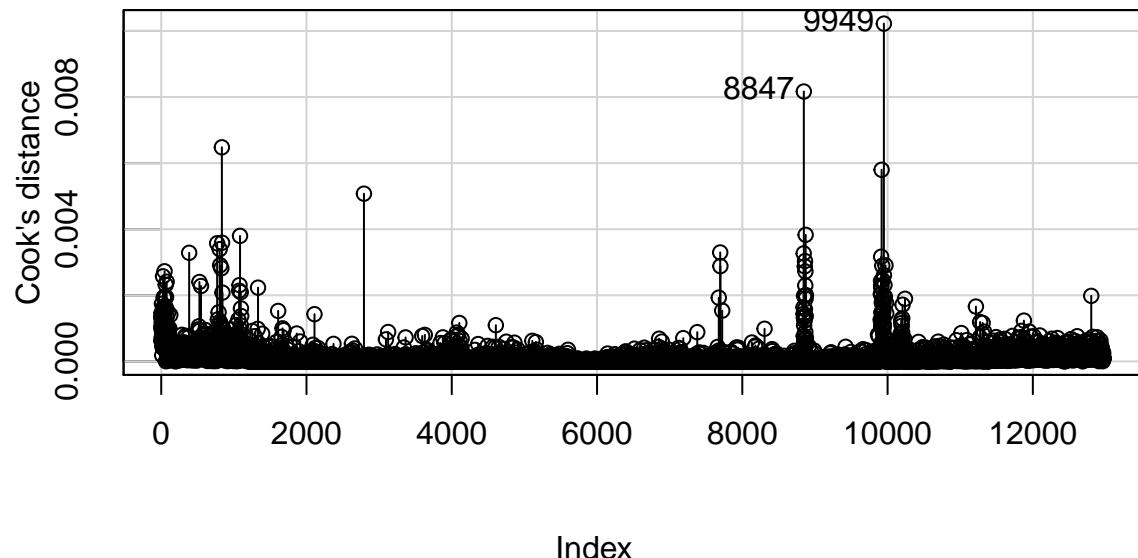
Plot 4:

```
## [1] 8847 11842
```

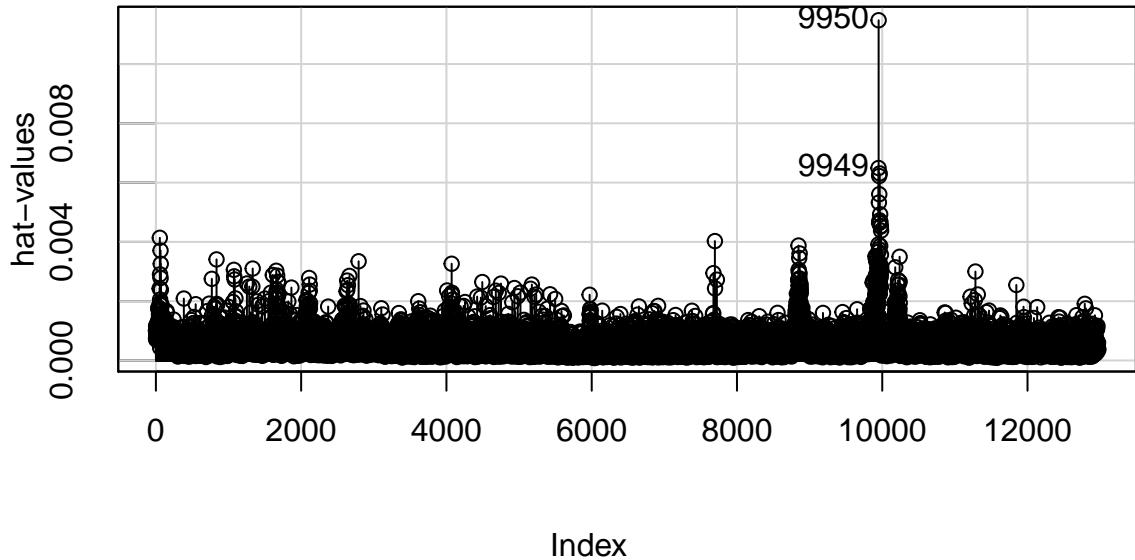


```
## [1] 46 8847
```

Plot 5:
Diagnostic Plots



Diagnostic Plots



Plot 6:

```

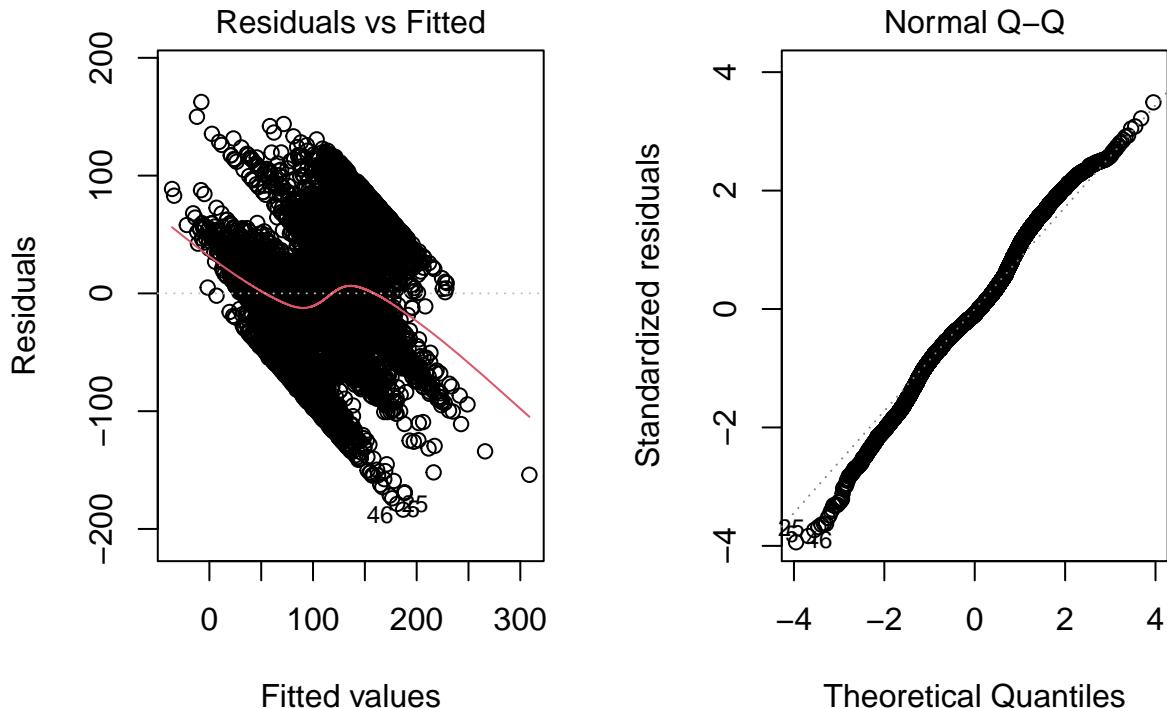
## 
## Call:
## lm(formula = sqrt(deaths) ~ I(retail_and_recreation_percent_change_from_baseline^{
##   3/2
## }) + sqrt(grocery_and_pharmacy_percent_change_from_baseline) +
##   I(parks_percent_change_from_baseline^{
##     1/3
## }) + log(transit_stations_percent_change_from_baseline) +
##   workplaces_percent_change_from_baseline + I(residential_percent_change_from_baseline^{(-2)}),
##   data = cacovid_mobilityGO)
## 
## Residuals:
##      Min       1Q   Median       3Q      Max 
## -183.594  -27.072   -3.883   27.049  162.524 
## 
## Coefficients:
## (Intercept)                         Estimate
## I(retail_and_recreation_percent_change_from_baseline^{\n  3/2\n}) 301.728
## sqrt(grocery_and_pharmacy_percent_change_from_baseline) -507.775
## I(parks_percent_change_from_baseline^{\n    1/3\n})        -63.876
## log(transit_stations_percent_change_from_baseline)        -43.319
## workplaces_percent_change_from_baseline                  -40.584
## I(residential_percent_change_from_baseline^{(-2)})        186.320
## 
## (Intercept)                         Std. Error
## I(retail_and_recreation_percent_change_from_baseline^{\n  3/2\n})      4.355
## sqrt(grocery_and_pharmacy_percent_change_from_baseline) 10.185
## I(parks_percent_change_from_baseline^{\n    1/3\n})        3.867
## log(transit_stations_percent_change_from_baseline)        1.274
## workplaces_percent_change_from_baseline                 7.075

```

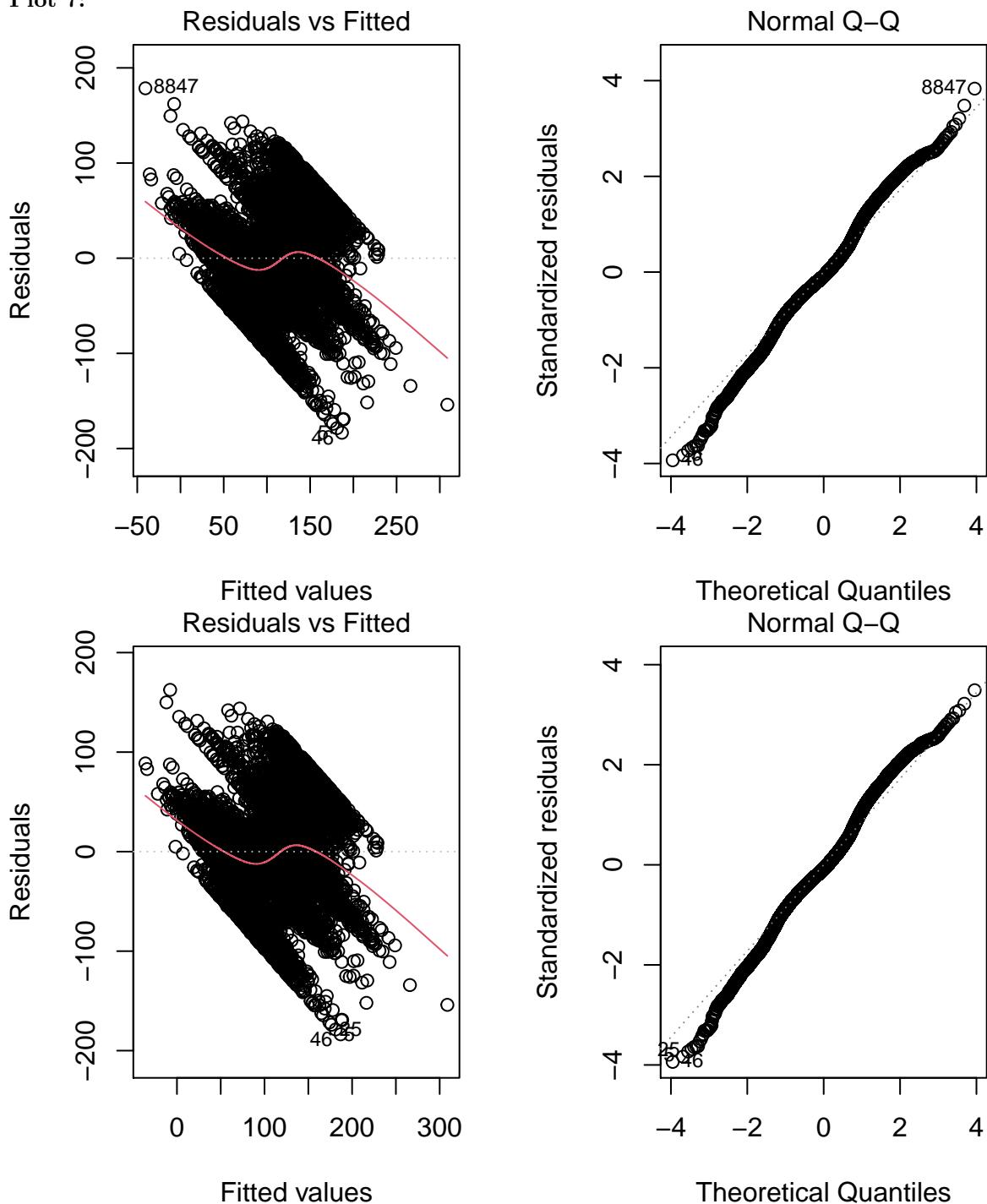
```

## I(residential_percent_change_from_baseline^(-2))           11.254
##                                         t value
## (Intercept)                                              28.106
## I(retail_and_recreation_percent_change_from_baseline^{\n 3/2\n}) 69.281
## sqrt(grocery_and_pharmacy_percent_change_from_baseline) -49.856
## I(parks_percent_change_from_baseline^{\n    1/3\n})          -16.516
## log(transit_stations_percent_change_from_baseline)        -34.005
## workplaces_percent_change_from_baseline                  -5.736
## I(residential_percent_change_from_baseline^(-2))          16.557
##                                         Pr(>|t|)
## (Intercept)                                              < 2e-16
## I(retail_and_recreation_percent_change_from_baseline^{\n 3/2\n}) < 2e-16
## sqrt(grocery_and_pharmacy_percent_change_from_baseline) < 2e-16
## I(parks_percent_change_from_baseline^{\n    1/3\n})          < 2e-16
## log(transit_stations_percent_change_from_baseline)        < 2e-16
## workplaces_percent_change_from_baseline                 9.89e-09
## I(residential_percent_change_from_baseline^(-2))          < 2e-16
##                                         ***
## (Intercept)                                              ***
## I(retail_and_recreation_percent_change_from_baseline^{\n 3/2\n}) ***
## sqrt(grocery_and_pharmacy_percent_change_from_baseline) ***
## I(parks_percent_change_from_baseline^{\n    1/3\n})          ***
## log(transit_stations_percent_change_from_baseline)        ***
## workplaces_percent_change_from_baseline                  ***
## I(residential_percent_change_from_baseline^(-2))          ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 46.64 on 12965 degrees of freedom
## Multiple R-squared:  0.4192, Adjusted R-squared:  0.4189
## F-statistic:  1559 on 6 and 12965 DF,  p-value: < 2.2e-16

```



Plot 7:



Appendix 3: R Code for World Bank

Base Data with World Bank imported, GDP, GDP growth, Hospital beds/1,000 ppl, Poverty= Poverty head count ratio at 1.90 a day(% of pop), CO2em: CO2 emissions (metric tons/capita), Air pollution: % Pop exposed to levels exceeding WHO guidelines,

```
x <- covid19()

## We have invested a lot of time and effort in creating COVID-19 Data Hub, please cite the following w
##
## Guidotti, E., Ardia, D., (2020), "COVID-19 Data Hub", Journal of Open
## Source Software 5(51):2376, doi: 10.21105/joss.02376.
##
## A BibTeX entry for LaTeX users is
##
## @Article{,
##   title = {COVID-19 Data Hub},
##   year = {2020},
##   doi = {10.21105/joss.02376},
##   author = {Emanuele Guidotti and David Ardia},
##   journal = {Journal of Open Source Software},
##   volume = {5},
##   number = {51},
##   pages = {2376},
## }
##
## To retrieve citation and metadata of the data sources see ?covid19cite. To hide this message use 've

covid19<- covid19(level = 1, start = "2020-03-15", end = "2021-03-15",)
wb <- c("gdp" = "NY.GDP.MKTP.CD", "hosp_beds" = "SH.MED.BEDS.ZS", "gdp_grow" = "NY.GDP.MKTP.KD.ZG", "pove
wbdcovid <- covid19(wb = wb)

## We have invested a lot of time and effort in creating COVID-19 Data Hub, please cite the following w
##
## Guidotti, E., Ardia, D., (2020), "COVID-19 Data Hub", Journal of Open
## Source Software 5(51):2376, doi: 10.21105/joss.02376.
##
## A BibTeX entry for LaTeX users is
##
## @Article{,
##   title = {COVID-19 Data Hub},
##   year = {2020},
##   doi = {10.21105/joss.02376},
##   author = {Emanuele Guidotti and David Ardia},
##   journal = {Journal of Open Source Software},
##   volume = {5},
##   number = {51},
##   pages = {2376},
## }
##
## To retrieve citation and metadata of the data sources see ?covid19cite. To hide this message use 've
```

```
wbdcovid
```

```
## # A tibble: 94,751 x 42
## # Groups:   id [199]
##   iso_alpha_3 id     date      vaccines tests confirmed recovered deaths hosp
##   <chr>        <chr>    <date>    <dbl> <int>    <int>    <int> <int> <dbl>
## 1 AFG         AFG     2020-01-22     NA     NA      NA      NA     NA     NA
## 2 AFG         AFG     2020-01-23     NA     NA      NA      NA     NA     NA
## 3 AFG         AFG     2020-01-24     NA     NA      NA      NA     NA     NA
## 4 AFG         AFG     2020-01-25     NA     NA      NA      NA     NA     NA
## 5 AFG         AFG     2020-01-26     NA     NA      NA      NA     NA     NA
## 6 AFG         AFG     2020-01-27     NA     NA      NA      NA     NA     NA
## 7 AFG         AFG     2020-01-28     NA     NA      NA      NA     NA     NA
## 8 AFG         AFG     2020-01-29     NA     NA      NA      NA     NA     NA
## 9 AFG         AFG     2020-01-30     NA     NA      NA      NA     NA     NA
## 10 AFG        AFG    2020-01-31     NA     NA      NA      NA     NA     NA
## # ... with 94,741 more rows, and 33 more variables: vent <int>, icu <int>,
## #   population <int>, school_closing <int>, workplace_closing <int>,
## #   cancel_events <int>, gatherings_restrictions <int>,
## #   transport_closing <int>, stay_home_restrictions <int>,
## #   internal_movement_restrictions <int>,
## #   international_movement_restrictions <int>, information_campaigns <int>,
## #   testing_policy <int>, contact_tracing <int>, stringency_index <dbl>,
## #   iso_alpha_2 <chr>, iso_numeric <int>, currency <chr>,
## #   administrative_area_level <int>, administrative_area_level_1 <chr>,
## #   administrative_area_level_2 <lgl>, administrative_area_level_3 <lgl>,
## #   latitude <dbl>, longitude <dbl>, key <lgl>, key_apple_mobility <chr>,
## #   key_google_mobility <chr>, gdp <dbl>, hosp_beds <dbl>, gdp_grow <dbl>,
## #   poverty <dbl>, co2em <dbl>, pollution <dbl>
```

Only variables from WB and Confirmed and Death

```
wbcovdata<- subset(wbdcovid, select = c("date", "confirmed", "deaths", "iso_alpha_3", "administrative_a
f
fgdp<- as.integer(wbcovdata$gdp)

## Warning: NAs introduced by coercion to integer range

fgdp_grow<- as.integer(wbcovdata$gdp_grow)
fhosp_beds<- as.integer(wbcovdata$hosp_beds)
fpoverty<- as.integer(wbcovdata$poverty)
fco2em<- as.integer(wbcovdata$co2em)
fpollution<- as.integer(wbcovdata$pollution)

cleandata <- na.omit(wbcovdata)
cleandata

## # A tibble: 51,379 x 11
##   date      confirmed deaths iso_alpha_3 administrative_are~      gdp gdp_grow
##   <date>    <int> <int> <chr>      <chr>       <dbl> <dbl>
```

```

## 1 2020-03-11      12     1 ALB    Albania 1.53e10 2.24
## 2 2020-03-12      23     1 ALB    Albania 1.53e10 2.24
## 3 2020-03-13      33     1 ALB    Albania 1.53e10 2.24
## 4 2020-03-14      38     1 ALB    Albania 1.53e10 2.24
## 5 2020-03-15      42     1 ALB    Albania 1.53e10 2.24
## 6 2020-03-16      51     1 ALB    Albania 1.53e10 2.24
## 7 2020-03-17      55     1 ALB    Albania 1.53e10 2.24
## 8 2020-03-18      59     2 ALB    Albania 1.53e10 2.24
## 9 2020-03-19      64     2 ALB    Albania 1.53e10 2.24
## 10 2020-03-20     70     2 ALB    Albania 1.53e10 2.24
## # ... with 51,369 more rows, and 4 more variables: hosp_beds <dbl>,
## #   poverty <dbl>, co2em <dbl>, pollution <dbl>

```

Graphs to check for Normality and variance

```

economic<- lm(deaths ~ confirmed, gdp, gdp_grow, poverty, data= cleandata) # Economic
airqual<- lm(deaths ~ co2em, pollution, data= wbcovdata) #Air Quality

summary(economic)
summary(airqual)

```

Appendix 4: Exploratory analysis not used in final paper

Github Link: <https://github.com/oboechick/STAT632FinalProject>

Appendix 5: Data Variable Description

- **date** - Observation date
- **confirmed** - Cumulative number of confirmed cases
- **tests** - Cumulative number of tests
- **population** - Total population
- **latitude** - Latitude (Check to see if more than 1 since we are only using CA)
- **longitude** - Longitude (Check to see if more than 1 since we are only using CA)
- **school_closing** - 0: No measures - 1: Recommend closing - 2: Require closing (only some levels or categories, eg just high school, or just public schools - 3: Require closing all levels
- **workplace_closing** - 0: No measures - 1: Recommend closing (or work from home) - 2: require closing for some sectors or categories of workers - 3: require closing (or work from home) all-but-essential workplaces (eg grocery stores, doctors).
- **cancel_events** - 0: No measures - 1: Recommend canceling - 2: Require canceling gatherings_restrictions 0: No restrictions - 1: Restrictions on very large gatherings (the limit is above 1000 people) - 2: Restrictions on gatherings between 100-1000 people - 3: Restrictions on gatherings between 10-100 people - 4: Restrictions on gatherings of less than 10 people.
- **gatherings_restrictions** - 0: No restrictions - 1: Restrictions on very large gatherings (the limit is above 1000 people) - 2: Restrictions on gatherings between 100-1000 people - 3: Restrictions on gatherings between 10-100 people - 4: Restrictions on gatherings of less than 10 people.
- **transport_closing** - 0: No measures - 1: Recommend closing (or significantly reduce volume/route/means of transport available) - 2: Require closing (or prohibit most citizens from using it).
- **stay_home_restrictions** - 0: No measures - 1: recommend not leaving house - 2: require not leaving house with exceptions for daily exercise, grocery shopping, and “essential” trips - 3: Require not leaving house with minimal exceptions (e.g. allowed to leave only once every few days, or only one person can leave at a time, etc.).
- **internal_movement_restrictions** - 0: No measures - 1: Recommend closing (or significantly reduce volume/route/means of transport) - 2: Require closing (or prohibit most people from using it).
- **international_movement_restrictions** - 0: No measures - 1: Screening - 2: Quarantine arrivals from high-risk regions - 3: Ban on high-risk regions - 4: Total border closure.
- **information_campaigns** - 0: No COVID-19 public information campaign - 1: public officials urging caution about COVID-19 - 2: coordinated public information campaign (e.g. across traditional and social media).
- **testing_policy** - 0: No testing policy - 1: Only those who both (a) have symptoms AND (b) meet specific criteria (eg key workers, admitted to hospital, came into contact with a known case, returned from overseas) - 2: testing of anyone showing COVID-19 symptoms - 3: open public testing (eg “drive through” testing available to asymptomatic people).
- **contact_tracing** - 0: No contact tracing - 1: Limited contact tracing, not done for all cases - 2: Comprehensive contact tracing, done for all cases.
- **stringency_index** - Stringency of governmental responses.
- **retail_and_recreation_percent_change_from_baseline** - comparison of pre-Covid-19 pandemic to Covid-19 pandemic travel trends to destinations classified as retail and recreation
- **grocery_and_pharmacy_percent_change_from_baseline** - comparison of pre-Covid-19 pandemic to Covid-19 pandemic travel trends to destinations classified as grocery stores and pharmacies
- **parks_percent_change_from_baseline** - comparison of pre-Covid-19 pandemic to Covid-19 pandemic travel trends to destinations classified as outdoor parks

- **transit_stations_percent_change_from_baseline** - comparison of pre-Covid-19 pandemic to Covid-19 pandemic travel trends to destinations classified as transit stations
- **workplaces_percent_change_from_baseline** - comparison of pre-Covid-19 pandemic to Covid-19 pandemic travel trends to destinations classified as work places
- **residential_percent_change_from_baseline** - comparison of pre-Covid-19 pandemic to Covid-19 pandemic travel trends to destinations classified as residential

wb - World Bank Data

Source

<URL: <https://covid19datahub.io>>

References

Guidotti, E., Ardia, D., (2020), "COVID-19 Data Hub", Journal of Open Source Software 5(51):2376, doi: 10.21105/joss.02376 (URL: <https://doi.org/10.21105/joss.02376>).