Analyzing Government Responses to COVID-19

Anthony Zeimbekakis
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Abstract

The Coronavirus pandemic began in early 2020 and continues to impact the world at the time of writing. Without a developed vaccine throughout 2020, governments resorted to various measures in an attempt to slow the spread of the virus. Examples of these measures include school closings, travel bans, stimulus checks, social distancing guidelines, contact tracing, and masking policies. As vaccines began to roll out at the turn of 2021, many of these responses loosened as the world took steps towards normalcy. With a critical eye on the responses to the pandemic, it will be important to know which policies were most effective in combating spread of the virus. In the event of another pandemic in the future, governments around the world can utilize this information to implement effective policies that will keep as many people alive as possible. This analysis uses LOWESS and linear regression on the Oxford COVID-19 Government Response Tracker dataset in an attempt to show which policies may have been the most impactful.

Introduction

The Coronavirus disease has been plaguing the world for about a year and a half. There have been over 257 million cases of the virus worldwide, claiming just over 5 million deaths to make it one of the deadliest pandemics in history (Worldometer, 2021). Perhaps the most effective way to combat the virus is through a vaccine, as we have seen with many epidemics in the past. However, vaccines take time to develop, and naturally there was not one available for COVID-19 at the time of the outbreak. Vaccine development typically has a timeline of seven years, and there was initial development on a vaccine for the original SARS (severe acute respiratory syndrome) virus so human use was not unprecedented (BJC HealthCare, 2021). The process for the SARS-CoV-2 (COVID-19's virus) vaccine was compressed into about a year of intense development due to its critical importance (BJC HealthCare, 2021). Between COVID-19's introduction into the world and the authorization of vaccine use in December 2020, there were various government responses in an attempt to slow the virus as best we could. For instance, in the United States there were multiple early travel bans announced as well as border closures between their neighbors in Canada and Mexico (Ballotpedia, 2021). As well, relief packages containing stimulus checked were approved to financially support families (Ballotpedia, 2021). These are both examples of government action aiming to hold off COVID while vaccine development took place. How successful were these policies? Which policies were the most effective? Knowing the answers to these questions may be crucial in the unknown event of another pandemic.

Literature Review

There is some knowledge about this already developed. Hsiang et al. (2020) applied reduced-form econometric methods to find that anti-contagion policies significantly and substantially slowed the growth of early COVID-19 infections. They estimate that early infections of COVID-19 exhibit exponential growth rates of approximately 38% per day (Hsiang et al., 2020). The study also notes that some policies have different effects on different populations, but there was consistent evidence that the packages deployed to reduce rate of transmission achieved measurable health outcomes (Hsiang et al., 2020). Dergiades et al. (2020) used daily data from 32 countries to find that the greater the strength of government interventions at an early stage, the more effective they are at slowing and reversing the growth rate of deaths. In addition, they found that school closures had a significant impact on reducing the growth rate of deaths, though bundling policy interventions together proved more effective (Dergiades et al., 2020). Haug et al. (2020) assessed non-pharmaceutical interventions (NPIs) to find that a suitable combination of NPIs is necessary in curbing the spread of COVID-19. As well, they find that less disruptive and costly NPIs can be as effective as more intrusive and drastic measures such as a national lockdown (Haug et al., 2020).

Data Acquisition

For this analysis, I will be using the Oxford COVID-19 Government Response Tracker (OxCGRT). The OxCGRT provides a systematic cross-national, cross-temporal measure to help understand how government responses have evolved since the disease’s first spread (Hale et al., 2021a). The project has tracked government policies and interventions across a series of indicators to measure the extent of these responses (Hale et al., 2021a). Data is collected on a daily basis, updated in real time, and contains up-to-date information. There are 23 indicators of government response collected in the project (Hale et al., 2021a). There are 4 types of indicators: Ordinal, Numeric, Text, and Categorical (Hale et al., 2021a). For the purposes of this analysis, I will only be concerned with Ordinal indicators. Ordinal indicators measure policies on a scale of severity and intensity and are reported for each day they are in place (Hale et al., 2021a). The following table shows all the OxCGRT indicators:

ID	Name	Type	Targeted/ General?
Containment and Closure			
C1	School closing	Ordinal	Geographic
C2	Workplace closing	Ordinal	Geographic
C3	Cancel public events	Ordinal	Geographic
C4	Restrictions on gathering size	Ordinal	Geographic
C5	Close public transport	Ordinal	Geographic
C6	Stay at home requirements	Ordinal	Geographic
C7	Restrictions on internal movement	Ordinal	Geographic
C8	Restrictions on international travel	Ordinal	No
Economic Response			
E1	Income support	Ordinal	Sectoral
E2	Debt/contract relief for households	Ordinal	No
E3	Fiscal measures	Numeric	No
E4	Giving international support	Numeric	No
Health Systems			
H1	Public information campaign	Ordinal	Geographic
H2	Testing policy	Ordinal	No
H3	Contact tracing	Ordinal	No
H4	Emergency investment in healthcare	Numeric	No
H5	Investment in Covid-19 vaccines	Numeric	No
H6	Facial coverings	Ordinal	Geographic
H7	Vaccination Policy	Ordinal	Cost
H8	Protection of elderly people	Ordinal	Geographic
Vaccine Policies			
V1	Vaccine prioritisation	Categorical	No
V2	Vaccine eligibility/availability	Categorical	No
V3	Vaccine financial support	Categorical	No
Miscellaneous			
M1	Other responses	Text	No

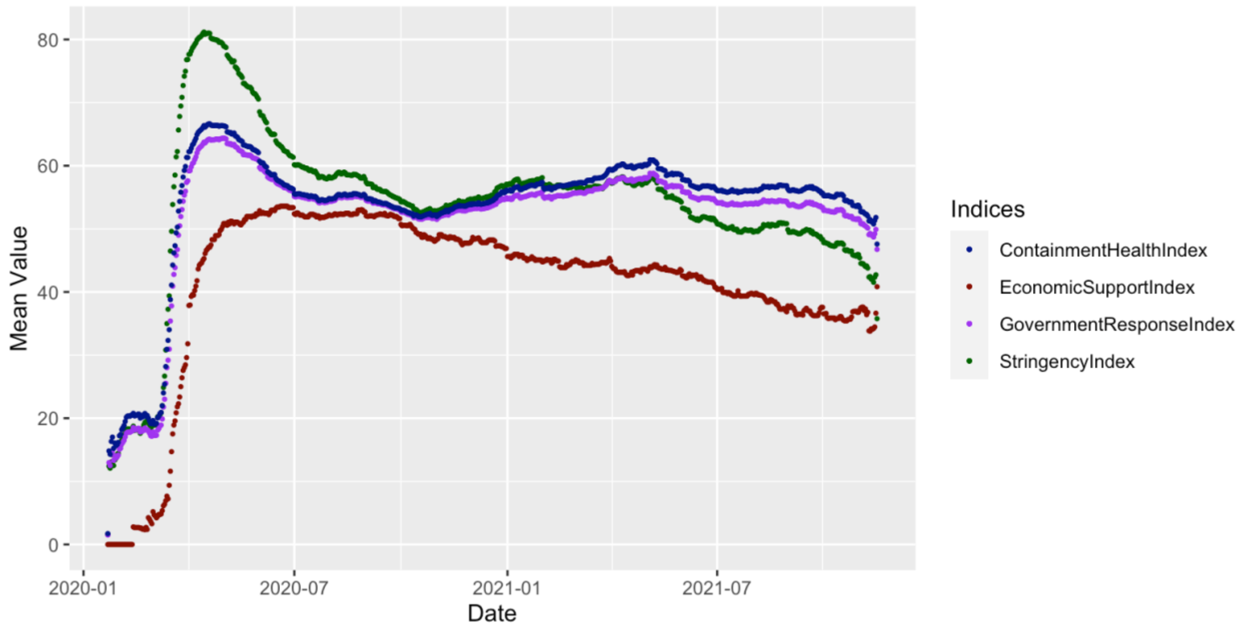
From “Variation in government responses to COVID-19” [7].

The dataset also contains subnational data. This means that it has data for the various states and provinces of the United States, Brazil, Canada, the United Kingdom, and China (Hale et al., 2021a). The analysis ignores these values, though it is important to note since you must consider these observations to avoid repeated data.

As for the measures themselves, there is some nuance to each government's response. The example considered by Hale et al. (2021a) is indicator C1, school closing. In some areas, all schools were shut down, while in others, schools may have remained open only for the children of essential workers and closed for the general public (Hale et al., 2021a). To alleviate this nuance, the OxCGRT team developed composite measures. These composite measures combine different indicators into general indices. The 4 composite policy indices are overall government response (all indicators), containment and health (all C and H indicators), stringency (all C indicators and H1), and economic support (all E indicators) (GitHub, 2021). Each of these is composed of their individual policy response indicators, and they are scored on a scale between 0 and 100 for simplicity (Hale et al., 2021a). It is important to note that these indices are not comprehensive measures of policy, and they do not necessarily provide information about how well policies are enforced or their appropriateness (Hale et al., 2021a).

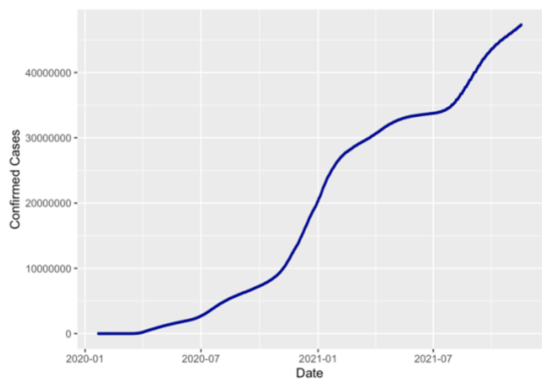
Preliminary Analysis

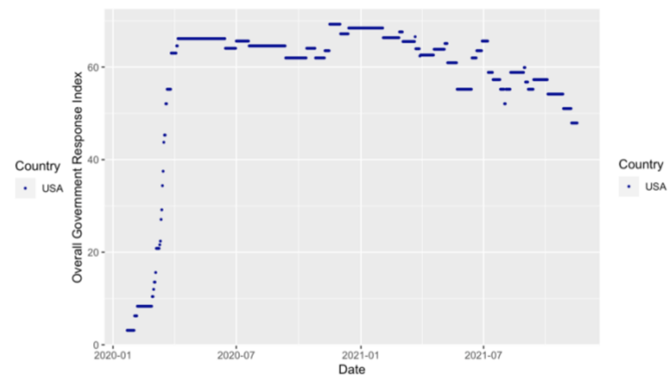
First, it would be useful to start with some exploratory analysis on the OxCGRT dataset. Below is a graph showing the mean values of each composite index from the beginning of the pandemic to now:

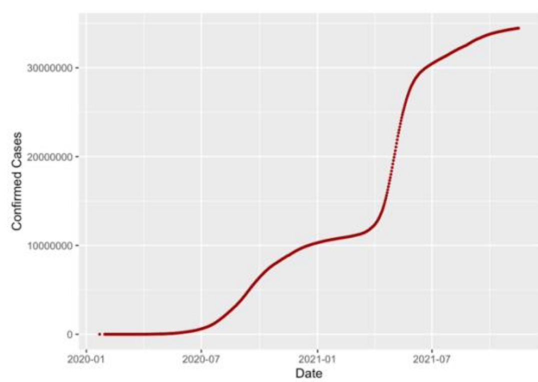


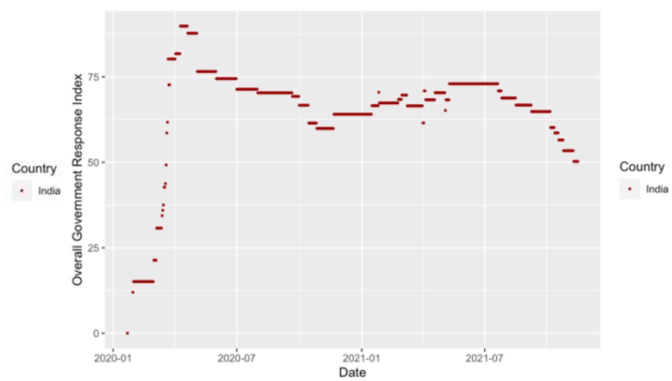
From this graph, we can learn a fair bit of information. We know that the stringency index was the most aggressive government response, reaching a mean value peak just above 80 in the early stages of COVID-19. As well, the economic support index was the least aggressive response throughout the ongoing pandemic. We can also note the large spike in the first half of 2020, which levels out to between about 40 and 60 for all indices for the rest of the data. There is also a slight increase heading into 2021 which perhaps denotes the various responses to the "second wave." Lastly, it is interesting to note that while vaccine rollouts began at the turn of 2021, the indices show that governments are still keeping many policies in place and we only see a drop-off at the very end.

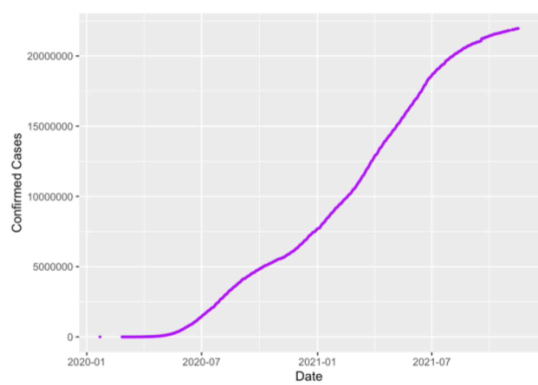
Something can also be learned from comparing confirmed cases of COVID-19 with the overall government response index. This is displayed for the 4 countries with the highest COVID-19 cumulative case counts: USA, India, Brazil, and the UK (Worldometer, 2021).

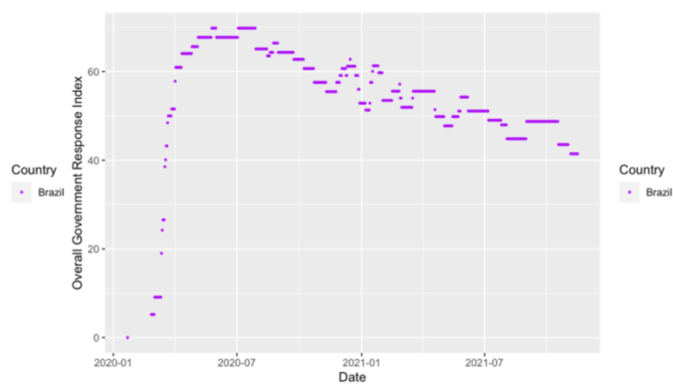

Confirmed Cases
40000000
30000000
20000000
10000000
0
2020-01
2020-07
2021-01
2021-07
Date
Country
USA

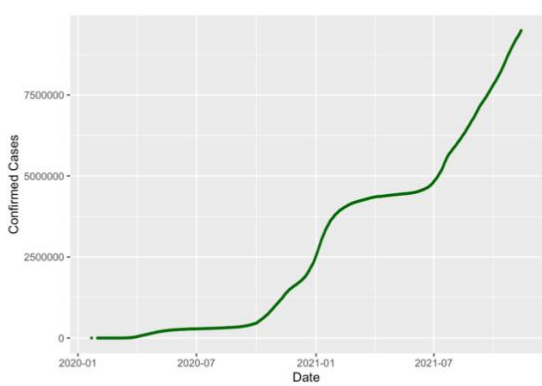

Overall Government Response Index
60
40
20
0
2020-01
2020-07
2021-01
2021-07
Date
Country
USA

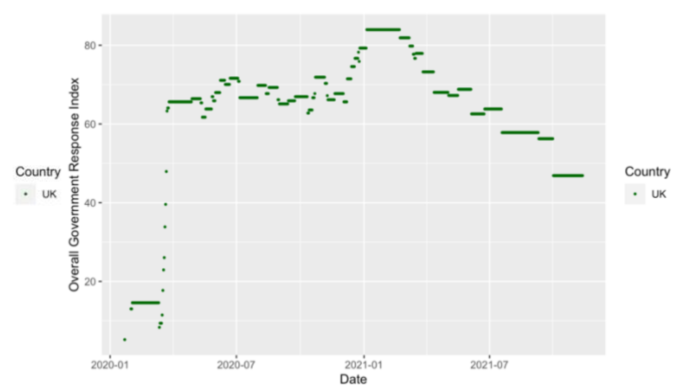

Confirmed Cases
30000000
20000000
10000000
0
2020-01
2020-07
2021-01
2021-07
Date
Country
India


Overall Government Response Index
75
50
25
0
2020-01
2020-07
2021-01
2021-07
Date
Country
India


Confirmed Cases
20000000
15000000
10000000
5000000
0
2020-01
2020-07
2021-01
2021-07
Date
Country
Brazil


Overall Government Response Index
60
40
20
0
2020-01
2020-07
2021-01
2021-07
Date
Country
Brazil

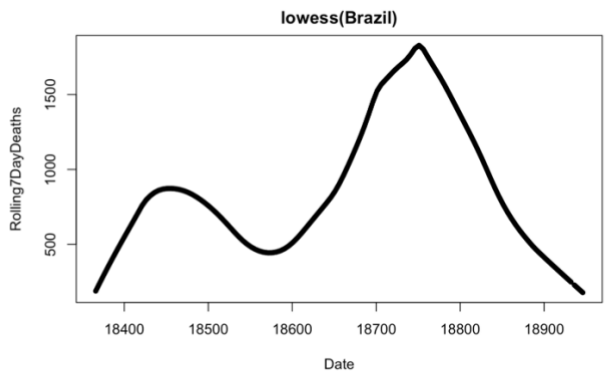

Confirmed Cases
7500000
5000000
2500000
0
2020-01
2020-07
2021-01
2021-07
Date
Country
UK

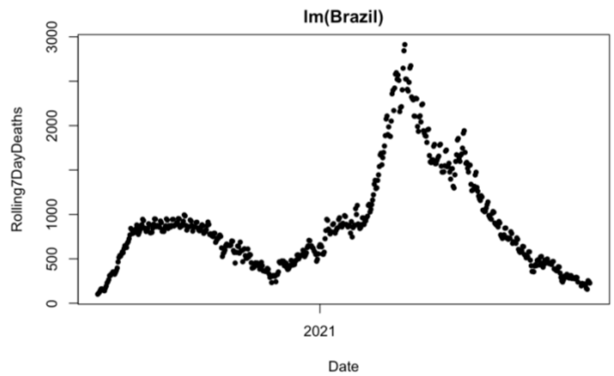

Overall Government Response Index
80
60
40
20
2020-01
2020-07
2021-01
2021-07
Date
Country
UK

For only 1 of the countries, Brazil, there is a fairly linear graph for confirmed cases. The others show rather clear slowing of the initial curve, such as India from the middle of 2020 to the end of the first quarter in 2021. The relationship between confirmed COVID-19 cases and overall government response index appears to be clearest in the United Kingdom. Early action to a mean value of between 60-70 corresponds to the slow growth of confirmed cases. Then, after the first wave of COVID-19 hits and cases level out, the government gradually eases their policies and the index falls at the start of 2021. This fall in index value corresponds with their current increase in cases, which has nearly doubled since they first began easing on their policies.

Method

The first task is to break the country data into their respective waves. The importance of waves, in my opinion, is to see the early impact of government responses. From the data, typically after the first wave the government response remained stable throughout due to COVID's consistent prevalence, even if the country was not experiencing a second wave. Therefore, I feel that identifying waves can help to remove some of the data where the government might have changed nothing about their response even though the wave had passed. As Hale et al. (2021b) describes, there is no definitive literature on what a "wave" is. However, there is a consensus that a wave is a phase of disease that is more substantial than a sporadic outbreak. It is characterized by a rising and falling phase, and therefore can be easy to identify. Much like Hale et al. (2021b), I opted for the smoothing regression LOWESS. LOWESS computes "smoothed" points, which act as a guard against deviant points (Cleveland, 1979). Various weights are calculated based on how large the local residuals are for each point. The larger the residuals, the lower the weight. The smaller the residuals, the higher the weight. There is also an assumption of smoothness that allows points near each (x_i, y_i) to be used in formatting the new y values. Essentially, smoothing regression helps us to avoid considering outliers as peaks of a curve. For instance, say a country is reports less cases over the weekend and once the week begins the number of cases spikes. Smoothing helps to alleviate that effect and provide clear, prolonged peaks. An application of this on our data is shown below:





After obtaining smoothed data for each country, we can determine where the waves are. I arbitrarily chose a wave to be if the point was the highest point within ±45 days. Using this I was able to calculate the waves for each country. Some countries, such as Brazil, only have 2 waves. Other countries, such as the United States, have 3 waves. In the data, we can eliminate the excess time where no waves are not prevalent.

For the regression, a simple linear regression was performed with the rolling 7 day death average as the dependent variable and various indices as the independent variable. The indices tested are the composite versions, as well as lag composite versions. Introducing lag can be important as studies have shown that policies typically have an impact 28 days after introduction (Li et al., 2020). Therefore, composite indices lagged 28 days were generated to be included in the analysis. As well, using log(Rolling7DayDeaths) can help to alleviate some of the variation and make for easier interpretation.

The hypotheses for these regressions are:

H_0: $\beta_1 = 0$

H_A: $\beta_1 \neq 0$

Results

The results for each simple linear regression are shown below:

GovernmentResponseIndex:

```
Call:
lm(formula = log(Rolling7DayDeaths) ~ GovernmentResponseIndex,
    data = Data)

Residuals:
    Min      1Q  Median      3Q     Max 
-5.8579 -1.5521 -0.0144  1.4929  5.2626 

Coefficients:
                         Estimate Std. Error t value            Pr(>|t|)    
(Intercept)             -2.244399   0.079927  -28.08 <0.0000000000000002 ***
GovernmentResponseIndex  0.067541   0.001292   52.29 <0.0000000000000002 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.127 on 15778 degrees of freedom
Multiple R-squared:  0.1477,    Adjusted R-squared:  0.1476 
F-statistic:  2734 on 1 and 15778 DF,  p-value: < 0.00000000000000022
```

ContainmentHealthIndex:

```
Call:
lm(formula = log(Rolling7DayDeaths) ~ ContainmentHealthIndex,
    data = Data)

Residuals:
    Min      1Q  Median      3Q     Max
-5.7547 -1.6040 -0.0221  1.5349  4.9556

Coefficients:
                        Estimate Std. Error t value            Pr(>|t|)
(Intercept)            -2.103326   0.084425  -24.91 <0.0000000000000002 ***
ContainmentHealthIndex  0.063265   0.001326   47.70 <0.0000000000000002 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.154 on 15778 degrees of freedom
Multiple R-squared:  0.126,	Adjusted R-squared:  0.126
F-statistic:  2276 on 1 and 15778 DF,  p-value: < 0.00000000000000022
```

StringencyIndex:

```
Call:
lm(formula = log(Rolling7DayDeaths) ~ StringencyIndex, data = Data)

Residuals:
    Min      1Q  Median      3Q     Max
-5.4373 -1.5978 -0.0598  1.4923  5.0293

Coefficients:
                 Estimate Std. Error t value            Pr(>|t|)
(Intercept)     -1.671021   0.068188  -24.51 <0.0000000000000002 ***
StringencyIndex  0.053607   0.001009   53.15 <0.0000000000000002 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.122 on 15778 degrees of freedom
Multiple R-squared:  0.1518,	Adjusted R-squared:  0.1518
F-statistic:  2825 on 1 and 15778 DF,  p-value: < 0.00000000000000022
```

EconomicSupportIndex:

```
Call:
lm(formula = log(Rolling7DayDeaths) ~ EconomicSupportIndex, data = Data)

Residuals:
    Min      1Q  Median      3Q     Max 
-4.8246 -1.6222 -0.0527  1.5712  5.6694 

Coefficients:
                      Estimate Std. Error t value            Pr(>|t|)    
(Intercept)          0.9015250  0.0324505   27.78 <0.0000000000000002 ***
EconomicSupportIndex 0.0197714  0.0005732   34.50 <0.0000000000000002 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.222 on 15778 degrees of freedom
Multiple R-squared:  0.07013,	Adjusted R-squared:  0.07007 
F-statistic:  1190 on 1 and 15778 DF,  p-value: < 0.00000000000000022
```

For each of the indices, their hypothesis tests for significance pass clearly, with miniscule p-values. However, the R-squared value shows that just each index alone is not very effective at explaining the variance in Rolling7DayDeaths. StringencyIndex is the highest, explaining just 15% of the variation in Rolling7DayDeaths. The worst is EconomicSupportIndex, but the values are all very weak. Their residual standard errors are all very similar in value as well, hovering around 2.1-2.2.

Simple linear regression was also performed for each country and their r-squared values were stored in a data frame. The summary statistics for these regressions are displayed below:

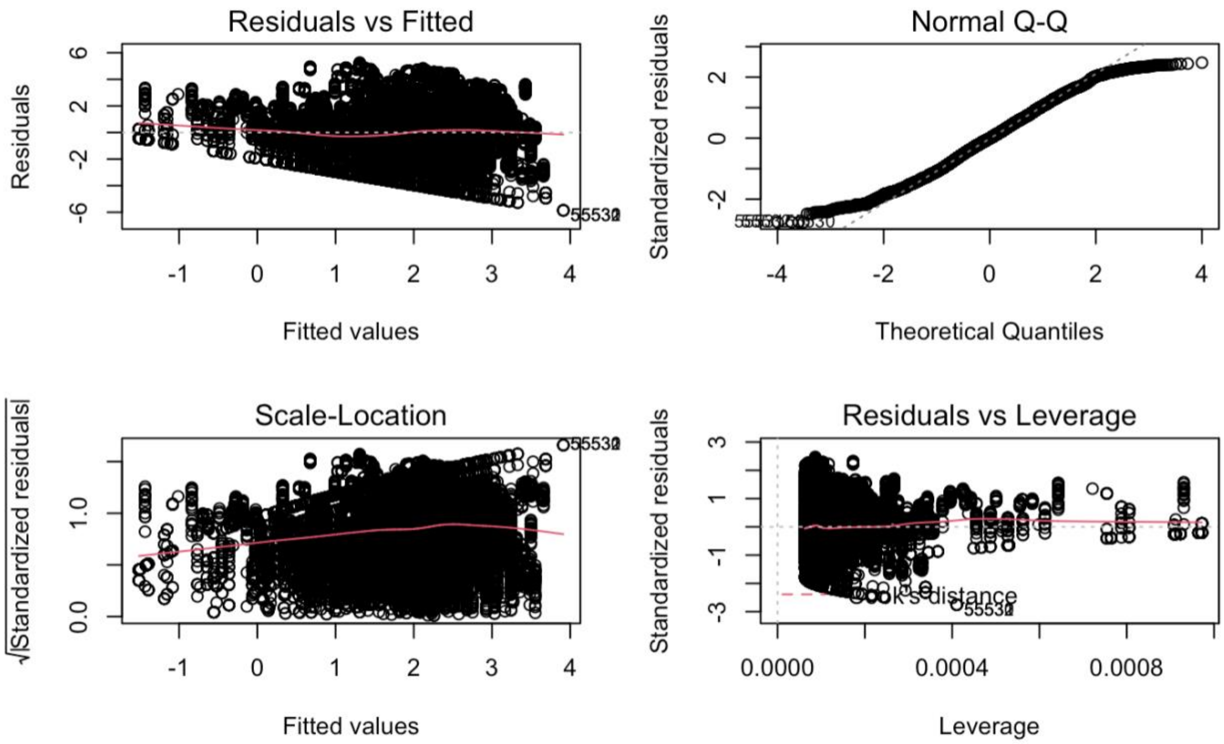
```
GovernmentResponseIndex
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
0.00000 0.02011 0.11717 0.19466 0.32515 0.77939

ContainmentHealthIndex
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
0.00000 0.02104 0.11713 0.19509 0.29775 0.77878

StringencyIndex
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
0.00000 0.02624 0.10746 0.18525 0.26769 0.84029

EconomicIndex
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
0.00000 0.00000 0.00000 0.06337 0.04139 0.71015
```

These values tend to agree with the general regression test. The means for the indices excluding EconomicIndex are all around 0.19, but the median values of 0.11 show that the values are skewed high. The majority of the tests explain little to no variation in COVID-19 deaths, though there are some interesting cases at the top. Notably, there are a cases where the variation is strongly explained by the government response, such as in Germany (stringency index, 0.84), Canada (overall government response index, 0.74), and Israel (containment health index, 0.77). Typically for these as well, the hypothesis tests for significance are passed, however due to the low R-squared values it is clear that there is a large amount missing from the analysis. There was also an interesting scenario with the lagging indices. My tests (although clearly lacking complexity and strength) found worse R-squared values than the normal indices. Obviously, R-squared is not the only way to measure a regression, but there was a clear difference between the two.

Discussion

Due to the simplicity of the tests, there is ultimately not much to gather from the analysis. As stated previously, although the hypothesis tests proved true there is still unexplained variance. I think there were several difficulties in regards to this analysis. For one, the composite indices are on a scale of 0 to 100. While this does allow for some simple analysis, it is likely best used for basic, high-level comparisons between governments. This also means that there is not much variance between values and the discreteness of the data adds further difficulties.

The assumptions for linear regression are likely where this analysis falls short. Consider the assumptions for the general GovernmentResponseIndex regression:



The first assumption on linearity is tough to tell. There seems to be a line blocking residuals from going too low, which might indicate a pattern. Homogeneity, the bottom left graphic, shows a large spread of values with a relatively horizontal line. This is already after a log transformation, so it's possible that this assumption is satisfied due to that. The assumption of normality is relatively met. The points veer off at the tails of the reference line but stick close in the middle. Lastly, and crucially, is independence. It is highly likely that many of these observations do not meet the independence requirement. Many COVID-19 cases are linked with one another, and it’s easy to see that the virus can spread to neighboring countries and influence that nation’s statistics. In addition, many countries may follow their allies and take similar government action (such as closing borders with each other) which would lead to dependent observations.

There was some analysis that aligns with scholarly research, such as the aforementioned cases of Germany, Canada, and Israel. With more time and resources, a more complex model could be built implementing time series knowledge, as well as holding for variables such as country GDP or abundance of hospitals. Also, although the tests may not be overtly conclusive, LOWESS regression was successfully implemented and some high-level analysis of government responses showed a pattern with how governments around the world have acted against the COVID-19 pandemic.

References

Ballotpedia. (2021). Federal Government Responses to the Coronavirus (COVID-19) Pandemic, 2020-2021.

BJC HealthCare. (2021). Timeline of the Covid-19 Vaccine Development.

Cleveland, W. S. (1979). Robust Locally Weighted Regression and Smoothing Scatterplots. *Journal of the American Statistical Association*, **74**(368): 829–836.

Dergiades, T., Milas, C., Mossialos, E., and Panagiotidis, T. (2020). Effectiveness of Government Policies in Response to the COVID-19 Outbreak.

GitHub. (2021). OxCGRT Coding Interpretation Guide.

Hale, T., Anania, J., Angrist, N., Boby, T., Cameron-Blake, E., Di Folco, M., Ellen, L., Goldszmidt, R., Hallas, L., Kira, B., Luciano, M., Majumdar, S., Nagesh, R., Petherick, A., Phillips, T., Tatlow, H., Webster, S., Wood, A., Zhang, Y. (2021). Variation in Government Responses to COVID-19 Version 12.0. *Blavatnik School of Government Working Paper*.

Hale, T., Angrist, N., Hale, A. J., Kira, B., Majumdar, S., Petherick, A., Phillips, T., Sridhar, D., Thompson, R. N., Webster, S. and Zhang, Y. (2021). Government responses and covid-19 deaths: Global evidence across multiple pandemic waves, *PLOS ONE* **16**(7): 1–14.

Haug, N., Geyrhofer, L., Londei, A., Dervic, E., Desvars-Larrive, A., Loreto, V., Pinior, B., Thurner, S. and Klimek, P. (2020). Ranking the effectiveness of worldwide covid-19 government interventions, *Nature Human Behaviour* **4**(12): 1303–1312.

Hsiang, S., Allen, D., Annan-Phan, S., Bell, K., Bolliger, I., Chong, T., Druckenmiller, H., Huang, L. Y., Hultgren, A., Krasovich, E., Lau, P., Lee, J., Rolf, E., Tseng, J. and Wu, T.

(2020). The effect of large-scale anti-contagion policies on the covid-19 pandemic, *Nature* **584**(7820): 262–267.

Li, Y., Campbell, H., Kulkarni, D., Harpur, A., Nundy, M., Wang, X. and Nair, H. (2021). The temporal association of introducing and lifting non-pharmaceutical interventions with the time-varying reproduction number (*R)* of sars-cov-2: a modelling study across 131 countries, *The Lancet Infectious Diseases*, **21**(2): 193–202.

Worldometer. (2021). Covid-19 Coronavirus Pandemic.