Modelling the Effectiveness of COVID-19 Response Measures

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Abstract

Since the first days of the COVID-19 pandemic, the non pharmaceutical interventions (NPIs) implemented by governments to suppress the spread of the virus have been under discussion of the public. Many of these NPIs are of significant impact on society. Most measures taken by governments however, lack scientific evidence of their effectiveness. Using the extensive amounts of data that have been collected during the pandemic, the effectiveness of several NPIs are modelled and interpreted in this research.

1 Introduction

In their confrontation with the COVID-19 pandemic, governments have introduced and implemented various non pharmaceutical interventions (NPIs). These interventions, or measures, aim to reduce the number of covid cases. However, most of the measures taken, are of great impact on society. Given this impact on society, many question whether these measures are worth the stain they leave on society, causing mental health problems [1] and impacting economies [2].

Some argue that the effect of covid response measures are not enough to justify the impact they have on society. Whether these arguments are valid or invalid, most measures have little scientific proof of their effectiveness. Most scientifically relevant studies towards the effectiveness of covid measures are often limited to certain countries and regions [3], or only focus on the effectiveness of specific measures [4]. To the best of our knowledge, an extensive scientific study on this topic has only been published once [5].

The vast amounts of data that have been collected during the covid-pandemic, can be used to research the effectiveness of covid measures taken by governments. In this research we aim to model the effect of NPIs on the reproduction rate of COVID-19 using historical data of measures taken by governments [6], as well as daily reports on the reproduction rate [7].

The dataset of measures taken by governments [6] contains data on 33 unique NPIs against covid. This research is limited to data from Europe, which results in information from 43 different European countries. However, the methodology proposed is not constrained by geographical features. Combining the NPI data with the daily reports leads to better insight in the effectiveness of certain NPIs, which in turn feeds the societal discussion on the matter.

2 Data

2.1 Resolving Skewness

Different countries approach the pandemic in different ways. Some governments proposed measures and restrictions that are only implemented in a single country for example. To get insight in how the data is distributed, the data is analysed. From this analysis, restrictions on the data are introduced, in order to limit the influence of any skewness in the dataset on the modelling approach.

```
Economic measures                                        1119
Limit public gatherings                                  1017
Closure of businesses and public services                1001
Strengthening the public health system                    511
                                                          ...
Limit product imports/exports                              18
Lockdown of refugee/idp camps or other minorities          15
Checkpoints within the country                              9
Humanitarian exemptions                                     1
```

Figure 1: Measure frequency

In figure 1 the total number of times that a measure has been implemented by any country is shown. From this distribution we learn that there are a few very specific measures that have only been introduced a limited amount of times. This also means that the amount of data for these mea-

Notebook available on: https://samtitar.github.io sures is very limited. This could in turn lead to incorrect generalisation on the data by a model that learns from this data.

```
Strengthening the public health system              43
Schools closure                                     43
Other public health measures enforced               43
Economic measures                                   43
                                                    ..
Full lockdown                                       10
Lockdown of refugee/idp camps or other minorities    5
Checkpoints within the country                       5
Humanitarian exemptions                              1
```

Figure 2: Measure country frequency

There are also measures that are only implemented in a specific set of countries. The distribution of the amount of countries that have introduced a measure is shown in figure 2. Again, the limited amount of data available in the datasets for some of these measures might result in inaccurate generalisations.

Based on these two distributions, three measures that are deemed to be underrepresented are removed from the data: *Humanitarian exemptions* (only implemented in a single country), *Checkpoints within the country* (only implemented in 5 countries) and *Lockdown of refugee/idp camps or other minorities* (only implemented in 5 countries). Modelling events that only very rarely occur in the dataset is ineffective as they could also impact the information for other events that occur more regularly.

2.2 Resolving Uncertainties

Inferring general rules from the data collected during the pandemic is greatly affected by the differences in methods of data collection between countries [8] [9]. This difference is most significantly present in the data on the reproduction rate. Figure 3 shows the difference between the reproduction rate in the United Kingdom over time and the reproduction rate in Sweden over time. The data from the United Kingdom show more sudden changes, while the data from Sweden shows only rough trends.

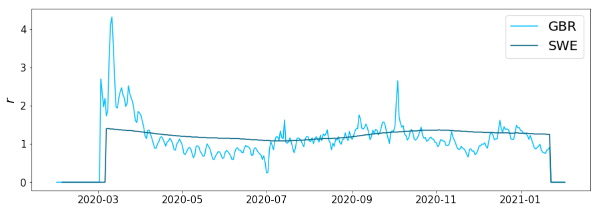

Figure 3: r in GBR and SWE before $MA(7)$

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To resolve this problem, a seven-day moving average ($MA(7)$) of the reproduction rate is introduced, resulting in the data shown in figure 4. The data from Sweden seemingly has not changed much, while the data from the United Kingdom shows more stable trends. This is important to the change in the reproduction rate Δr. Sudden changes are now much less impactful, while the overall trends remain.

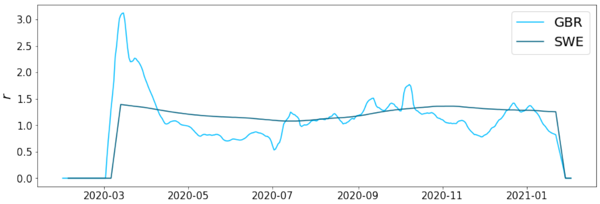

Figure 4: r in GBR and SWE after $MA(7)$

3 Methodology

In our approach we use a multiple regression model that learns to predict the change in reproduction rate (Δr) over a seven day period (r_{t+7}). The features for this model are the NPIs that are active at day t. At each timestep t the model is also provided with (1) the GDP per capita as an economic indicator, (2) the total population, (3) the population density, and (4) the total number of active measures. The model is provided with these features to control for their effect on the reproduction rate.

By interpreting the coefficients of the regression model, the effectiveness of the NPIs modelled can be extracted. Each coefficient describes a linear relation between whether an NPI is active and Δr.

4 Results

The trained model has learned to model the relation between NPIs and the reproduction rate of COVID-19 with a mean squared error (MSE) of 0.0819. In table 1 the coefficients of the trained model are shown. Based on these coefficients, the NPIs are ranked on effectiveness.

The table also shows the the coefficients for the covariate features (i.e. GDP per capita, Population size, Population density and the number of active measures). These covariate features have little to no impact on the Δr, as indicated by the relatively small coefficients. The dashed line indicates the border where the coefficients are larger in absolute value than the intercept.

Rank	NPI	Coefficient (towards Δr)
1	Health screenings in airports and border crossings	-0.1391302
2	Amendments to funeral and burial regulations	-0.1087074
3	International flights suspension	-0.0895136
4	Changes in prison-related policies	-0.0810768
5	Limit product imports/exports	-0.0803689
6	State of emergency declared	-0.0791075
7	Awareness campaigns	-0.0770310
8	Partial lockdown	-0.0598347
9	Closure of businesses and public services	-0.0563162
10	Border closure	-0.0539507
11	Mass population testing	-0.0499771
12	Limit public gatherings	-0.0475034
13	Curfews	-0.0464392
14	Surveillance and monitoring	-0.0433568
15	Border checks	-0.0399447
16	Isolation and quarantine policies	-0.0377187
17	General recommendations	-0.0371980
18	Schools closure	-0.0369984
19	Strengthening the public health system	-0.0321312
20	Military deployment	-0.0318143
21	Additional health/documents requirements upon arrival	-0.0309593
22	Visa restrictions	-0.0277604
23	Domestic travel restrictions	-0.0259970
24	Emergency administrative structures activated or established	-0.0224603
25	Requirement to wear protective gear in public	-0.0221275
26	Testing policy	-0.0186716
27	Psychological assistance and medical social work	-0.0151096
28	Economic measures	-0.0148937
29	Full lockdown	-0.0092277
30	Other public health measures enforced	-0.0016979
31	**Population density**	-0.0000089
32	**GDP per capita**	-0.0000001
33	**Population size**	-0.0000000
34	**Number of active measures**	-0.0000000
-	Intercept	0.0152948

Table 1: The linear coefficient for each NPI

5 Discussion

The proposed method of modelling the effect of NPIs on Δr for the COVID-19 pandemic is able to predict Δr with a MSE of 0.0819. Each NPI is then ranked on effectiveness using the coefficients of the trained model. From the coefficients three findings will be discussed.

5.1 Covariate Features

The coefficients of the trained model suggest that all four covariate features provided to the model have a neglectable effect on Δr, compared to the coefficients of other features. This suggests that regardless of the measurable characteristics of a country, a NPI implemented in any country should be as effective as in any other country.

This deduction is limited to countries within Europe however, as the research conducted is limited to data from Europe. The deduction is also only based on measurable differences between countries (such as GDP per capita and population density). Cultural difference between countries for example, are not considered, and might have a more notable effect on the effectiveness of NPIs.

5.2 Border Control

Four of the ten most effective NPIs described by the modelling approach, are based on limitations and screenings of movements across country borders. Research towards the effectiveness of border closures [10] suggests that border closres during the early phases of the COVID-19 pandemic are notably more effective than in later stages of the pandemic.

The coefficients produced by the modelling approach in our research might be a result of skewness in the date span of border control measures. Many border restriction were only implemented during earlier stages of the pandemic. In a more accurate approach these variables should also be controlled for.

5.3 Nonphysical Measures

Most *nonphysical* measures, or measures that are not directly targeted at reducing the number of covid cases (such as *Economic measures* and *Emergency administrative structures activated or established*) are ranked lower by our modelling approach. These measures should be unlikely to correlate with the reproduction rate. Their coefficients are not neglectable however.

This is likely explained by the nature of these measures. As supported by figures 1 and 2 in section 2, these measures (specifically *economic measures*) are very frequently implemented. As a result of this, these measures overlap substantially with other, more physical or direct measures. Which in turn results in correlation with these direct measures, and thus correlation with r.

6 Conclusion

Through the modelling approach proposed in this research, the effectiveness of various NPIs are ranked. The effectiveness of an NPI is expressed in the contribution towards a lower Δr of an NPI. A discussion, based on the results of this approach shows that the results should be interpreted with care. Various caveats and their implications are described and discussed.

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