# Effects of lockdown stringency on trust in government and mental well being in times of COVID-19, based on PsyCorona and oxCGRT data sets

Bachelor's Project Thesis

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**Abstract:** Past research demonstrated that the COVID-19 pandemic and lockdowns caused by it had significant effects on mental well being and trust in government. This study aims to examine how those effects differ depending on the stringency of lockdowns in different palaces. The data used in the analysis comes from the longitudinal survey study PsyCorona which gathered responses from participants all over the world since the beginning of the pandemic and from the Oxford COVID-19 Government Response Tracker. The study used among other linear regression, principal component analysis, mediation analysis and others. The study has found a positive correlation between mental well being and trust in government. It found that stringency had a positive effect on trust in government and a negative effect on mental well being. It further found that the frequency of changes to stringency has a positive impact on trust in government while, its effects on mental well being differed depending on the period on which they are measured. Lastly the study used LSTM models in order to examine whether the individual trajectories of mental well being and trust in government can be predicted. The results were significantly better than the persistence model, which predicts no change in values.

## 1 Introduction

COVID-19 was first identified in December 2019 in Wuhan, China and in March 2020 its outbreak was declared a global pandemic by the World Health Organisation. By the end of June 2021, there were over 180 million confirmed cases and almost 4 million confirmed deaths. In order to prevent the spread of the virus, most governments implemented various preventive measures, including but not limited to limitations to movement within and between countries, stay at home orders, mask mandates and other lockdown style policies.

While the lockdown style policies were necessary in order to prevent the spread of the virus and decrease the number of infections and deaths, they also had significant effects on mental well being of people affected by them and trust in governments implementing them.

A meta-analysis (Rajkumar, 2020), combining studies from across the world, published in April 2020 revealed that there is a significant increase in frequency of mental health problems, especially anxiety and depression caused by COVID-19 pandemic. It found that while being female, being a student, having COVID-19 symptoms or poor health in general increased the frequency of mental issues, the availability of accurate information and practising of preventive measures reduced it. It further reported that factors such as unpredictability, uncertainty, seriousness of ones disease, misinformation and social isolation contributed to stress in particular. It revealed that patients and their families, people with preexisting conditions (both physical and psychological), older adults, migrant workers, homeless and pregnant women were populations at higher risk of mental health issues. It showed that being economically affected by the pandemic and measures to prevent it affected ones well-being, caused fear and panic and were associated with behaviours such as hoarding. It further revealed that anxiety about ones health was exacerbated by misleading media representations and was associated with decline of trust to government and other people.

Kontoangelos et al. (2020), reviewed papers from the beginning of 2020 and showed that multiple groups were at special risk of mental health problems. This included people with preexisting mental health issues and healthcare workers. Moreover it showed that factors such as peer support, therapy and early mental health interventions were able to improve persons mental health, while exposure to misinformation made it deteriorate.

Another review of evidence available in May 2020 (Vindegaard and Benros) showed that while mental health worsened during the pandemic, there was no significant difference at the beginning of the pandemic and 4 weeks into it. It further identified women, healthcare workers and people with poor mental health prior to COVID as particularly vulnerable groups.

A meta-analysis based on 25 studies, published in January 2021 (Prati and Mancini) revealed that when combining results from studies done up to that point, lockdowns had a small but significant effect on anxiety and depression, while other factors such as social support, loneliness, distress, negative affect and suicides weren't statistically significantly different. The study further revealed that while such trends were true in aggregate, the responses were strongly heterogeneous. While the modal response was resilience to mental health problems, there were groups in a population affected much more strongly. It further revealed that some of the moderating factors affecting the effect of lockdowns was a person's attitude towards the lockdown, sense of support from others, as well as confidence in public health measures. The study further found that the number of deaths recorded didn't have a significant effect on people's mental health. However the study had multiple limitations, including not accounting for stringency of lockdowns, their length and only examining the initial lockdowns.

Several studies reported an increase in trust towards government in the early stages of the pandemic. In particular Thoresen et al. (2021) reports that in Norway while there was no significant difference in the levels of trust in government of the general population, there was a significant for people personally affected by COVID-19. It also reported that higher worry about the pandemic was a predictor of low trust in government. Lim et al. (2021) reports that 97.9% of people in Singapore believed that information from government sources was trustworthy. Sibley et al. (2020) and Goldfinch et al. (2021) both report that trust in government in early stage of the pandemic increased in Australia and New Zealand. In particular 80% agreed that the government is trustworthy and 75% reported that the handling of COVID-19 by their government increased their trust in them. However as mentioned by Sibley et al. (2020) and Goldfinch et al. (2021) the effect may be temporary and not hold over longer period of time, which may be partly caused by the negative economic ramifications of lockdowns. Moreover Sibley et al. (2020) further notices that those results are aggregate, and despite the mean effect on trust being positive, there may be specific subsets of the population, who's trust in government has been reduced.

Multiple studies also pointed out that high trust in government can be a factor increasing compliance to the restrictions imposed due to lockdowns (Lim et al., 2021) (Saechang et al., 2021) (Goldfinch et al., 2021) (Harring et al., 2021) , especially for lockdowns that are not strictly monitored and enforced (Sibley et al., 2020). This has been also shown in previous epidemics such as H1N1 Gilles et al. (2011) . Interestingly Saechang et al. (2021) showed that negative effects of lack of trust to the government on compliance can be moderated by a high level of trust toward health professionals. The study showed that in Thailand, despite low levels of trust towards the government, people still complied to the restrictions voluntarily at high rates. Another explanation for compliance and support for restrictive measures was given by Harring et al. (2021). By considering the pandemic as a social dilemma it was explained that if on top of not trusting the government people also lack trust to other people, they may still prefer restrictive measures, since they don't trust other people to change their behaviour to reduce the spread of the pandemic and because of that an external intervention is needed.

Gustavsen et al. (2014) proposed that trust in government reflects perceived governmental performance. This is corroborated by the findings of Goldfinch et al. (2021) which showed that voting for the party currently in power, which likely correlates with perceived performance, was a predictor of trust towards the government. On top of that multiple factors were found to predict individuals trust towards government, namely higher education and higher income (Goldfinch et al., 2021). Sibley et al. (2020) further suggested that both trust in government and belief in conspiracy theories may be caused by pursuing psychological comfort, by different types of people. Moreover self-reinforcing nature of trust in government and effective response to the pandemic was suggested by (Harring et al., 2021) (Saechang et al., 2021) (Goldfinch et al., 2021). They suggested that lack of trust may force governments to impose stricter measures (since the population is unlikely to comply to unenforced measures), which can further damage the trust between the government and the population.

O'Hara et al. (2020) showed that trust in government is both affected by and affects mental health. It showed that people with higher mental fatigue, are more likely to not comply with public health measure, while also showing that negative effects of lockdowns on mental health can be moderated by trust in the government enforcing it, so that negative effects of lockdowns are smaller for people who trust in government. Lim et al. (2021) further showed that while trust in government increased ones perceived level of threat of the pandemic (which likely increases compliance with public health measures), it also reduces the perceived risk of infection.

### 1.1 What remains to be studied

Before mentioned studies had demonstrated the COVID-19 pandemic and lockdowns created by it had significant effects on people's mental well being and their trust in government in places all over the world. They further demonstrated that mental well being and trust in government further affect each other directly as well as mediators in relationships with other variables such as a presence of a lockdown. However while many studies examined the effects that lockdowns had on both trust in government and mental well being, none of them examined how those relationships are affected by stringency of lockdowns. Because of that gap in research, they main research question posed by this paper is "How does the stringency of lockdowns affect mental well being and trust in government". Since it has already been demonstrated that the mental well being and trust in government moderate each other in order to fully answer the research question, interaction effects between them will also be explored. Lastly since all of the past studies only examined aggregate trends and not individual trajectories of peoples mental well being and trust in government this study will also examine whether future values of mental well being and trust in government can be predicted based on past data. This leads to the second research question "Is it possible to predict individuals trust in government and mental well being based on past data?". This study aims to combine the data from the psyCorona dataset concerning mental health of participants throughout the pandemic and Oxford Coronavirus Government Response Tracker (oxCGRT) in order to answer the research questions.

## 2 Methods

The study aims to examine the relationships between the mental well being of individuals, their trust in governments ability to deal with COVID-19 and the stringency of the lockdowns in the places they live. In order to do that, the study is divided into two parts. In the first part, statistical tools such as linear regression, mediation analysis and principal component analysis are used to examine the relationships between the listed variables. This part will allow us to gather interpretable results which will allow for a better understanding of the data and for the answering of part of research questions. The second focuses on creating machine learning models that given a sequence of values for the listed variables will try to predict the future values of individuals mental well being and trust in government. This part will examine how well, given just the past values of mental well being, trust in government and stringency, one is able to predict their future values. This will further provide s information about how those values vary over time.

### 2.1 Data sources

#### 2.1.1 PsyCorona

The data about the mental well-being and trust in government of individuals was derived from the PsyCorona study (Kreienkamp et al., 2020). The study conducted rounds of questionnaires, initially at a weekly and later on a monthly basis. The questionnaires asked participants questions about their mental well being, activities, beliefs and many others. The dataset used by this study consisted of answers from 64246 individual participants, all of which answered at least the baseline survey. According to the PsyCorona project, approximately half of those participants were recruited via paid panels. Participants for the panels were selected in a way to ensure representatives across different dimensions such as gender, while the other half was composed of voluntary respondents (the representatives of population was not enforced for the volunteers). Each participant responded to the baseline survey and any combination of followup waves (there weren't any particular restrictions on gaps in responses etc).

The initial dataset consists of 1369 variables, one for each question in each wave (so if a question was asked in the baseline and 9 waves, there are 10 variables about it). Some of the questions are part of the baseline survey, while others were present both in the baseline survey and in the followups. All of the wave questions are repeated over multiple waves. However different waves have different sets of questions, since new questions were being added and removed throughout the study.

#### 2.1.2 Oxford COVID-19 Government Response Tracker (OxCGRT)

In the analysis, the data from the Oxford COVID-19 Government Response Tracker (OxCGRT) (Hale et al., 2020) was also used. OxCGRT is a project conducted by the Blavatnik School of Government from the Oxford University which tracks the responses of governments in 180 countries to the COVID-19 pandemic. They track 20 different indicators in different areas, such as containment policies, economic policies and health policies. Based on them 4 different indexes are constructed. For all the indexes, all the variables which they include are recorded on different ordinal scales and are later combined into a single index (ranging in values between 0 and 100).

The stringency index combines measures of 'lockdown style' policies which primarily restrict people's behaviour. The index combines the values of the following 9 measures: closings of schools, closings of workplaces, cancellations of public events, restrictions on gatherings, closings of public transport, stay at home orders, restrictions on internal movement (within a country), restrictions on international travel and the public information campaigns.

The containment and health index includes all the variables from the stringency index and additionally variables focused on the handling of the health consequences of covid. Those include testing policy, contact tracing, policy on facial coverings, vaccination policy and the approach to protecting the elderly.

The economic support index includes 2 variables concerning weather the government provided forms of income support as well as debt/contractor relief.

The final government response index is a combination of the health and containment index and the economic support index.

The stringency index has been chosen to be used for the rest of the study. It contains all the variables that create restrictions on people's behaviour and force them to change their routines. Other indexes could also affect the trust in government and mental well being (for example for people struggling financially, the income support may be more important than weather they can travel abroad freely), but they are outside the scope of this study.

The dataset can be accessed through the following URL: `https://raw.githubusercontent.com/OxCGRT/covid-policy-tracker/master/data/timeseries/stringency_index.csv`

## 2.2 Data preparation

#### 2.2.1 PsyCorona column and row selection

I selected only the variables related to the research question. Variables that stayed included: all the affect variables that were present in all of the waves (anger, boredom and love variables were removed, since they weren't present in some of the waves), trust in governments ability to respond to COVID-19 variable and the country of origin (which is necessary to connect PsyCorona and oxCGRT datasets). Since both the trust and affect variables were ordinal , they were mapped onto a numerical scale from 1 to 5 (where 1 represented the lowest possible response, while 5 represented the highest).

All of the affect variables were replaced with a single mental well being index variable. It was created by taking the weighted sum of all the affect variables (were calmness, energy, inspiration and relaxedness were taken with a positive sign, while anxiety, depression, exhaustion and nervousness were taken with a negative sign).

Due to the fact that the date of the observation is estimated based on the wave number (at least one of which is needed for the baseline date estimation), all the rows in which no wave questionnaire was answered were removed.

### 2.2.2 Flattening the data

The problem with using the remaining dataset for time series forecasting, is that most rows still had many missing values and there were very few participants who responded in most of the waves. Because of that, a time series analysis would prove to be difficult in the current form of the dataset. Because of that the dataset was transformed in the following way. Instead of each data point representing an individual participant, each data point represented a series of N consecutive responses by an individual participant. Each row consisted of N columns representing the mental well being index at consecutive time points, N columns representing the trust in government at consecutive time points, ID of the participant, their country of origin, and the number of the earliest wave represented in the row. In the rest of the paper I will use the word "depth" to described how many time steps are represented in a row of a given dataset (for example depth 2 implies measurements at time X and X-1 where X is a number of a questionnaire wave). The relation between the depth N and the size of the resulting dataset is depicted in figure A.1, while the number of unique participants included in the dataset is depicted in figure A.2 (both in the appendix).

### 2.2.3 Mapping the oxCGRT dataset

The oxCGRT data was added to the flattened data sets by mapping each row to a stringency values based on the country variable and estimated time of response. Since Armenia and Montenegro were not present in the oxCGRT dataset all the responses from those countries were discarded.

Since the dates at which the wave questionnaires were sent were known, the dates were assigned by a simple mapping of wave number to the date. Since the baseline is not connected to any particular date and represents the first time a person filled the questionnaire, a different procedure had to be used for it. Since the wave measurement s are followups to the baseline it can be deduced that the baseline took time sometime between the first wave measurement present for the person and the wave before. In the case of when a person has responded to the first wave, the date of the baseline is approximated to be between the first wave and the start of the study. With the data it is not possible to get the exact date of the baseline measurement, however the date in the middle of the period when it could have been conducted was selected as an approximation.

Based on such a combination of date and country, each time step for each person was assigned a stringency value from the oxCGRT dataset.

### 2.2.4 Additional stringency metrics

On top of the absolute values of stringency in all countries on all dates, some additional variables based on stringency were added. Each variable described below was computed for a time frame of both a week and a month before the estimated time of the response. The following variables were added:

Mean stringency over a period of time, standard deviation of the stringency over a period of time, number of times stringency changed in a period of time, sum of absolute changes in stringency over a period of time, difference in stringency between the beginning and the end of the period of time.

The mean variables are supposed to account for the fact that a longer experience of a strict lockdown may have stronger effects on ones well being and trust. The difference in stringency between the beginning and end of the period of time, might be able to capture effects of the direction of changes over time (for example lightening of lockdowns may induce optimism and result in better mental well being). All the other variables (standard deviation, sum of absolute changes, number of changes) are different measures, all of which are supposed to quantify the volatility of the lockdown at a given place (high value of any of those implies that the rules are constantly changing).

## 2.3 Statistical analysis

### 2.3.1 Selecting stringency metrics

Due to the fact that some of the stringency variables measure highly related concepts, there may be a high degree of multicolinearlity. In order to minimise the distorting effect of colinearity on the interpretability of the later results the relations between the stringency variables will be analysed. In order to ensure the best results possible, the variables used in alter parts of the study will be selected through a data-driven approach, which examines the relationships between the stringency variables as well as their relationships with trust in government and mental well being. The degree of correlation between the variables and ascendant hierarchical variable clustering will both be used in order to group the variables into clusters. Ascendant hierarchical variable clustering is a method that starts with single variable clusters after which, at each step it combines the most similar clusters (based on "distance" between clusters which for quantitative variables is defined as squared correlation between the variable and the cluster centre), until all the variables are combined into a single cluster.

Next a single variable from each cluster will be selected, in order to represent the entire cluster. In order to do that additional variables will be added, namely the first component from a principal component analysis (PCA) of the cluster. It is a linear combination of all the variables in a cluster that is supposed to capture the highest amount of variance possible. Next all the individual variables and the PCA will be compared based on their ability to predict mental well being and trust in government. That will be done by running linear regressions for each of the variables in the cluster (where that variable is the only predictor) and comparing the $R^2$ values from those regressions. In cases where one variable will be the best predictor for both dependent variables it will be selected. If the dependent variables are best predicted by different predictors, the one with the highest multiple of $R^2$ values will be selected.

### 2.3.2 Linear regression

Once the stringency metrics have been selected linear models will be created in order to examine the relationships between the variables. There will be 2 separate analyses, one for models predicting mental well being and one for models predicting trust in government. In each analysis 2 separate models will be created, one with interactions between trust in government/mental well being and the stringency variables and one without them. The 2 models will be created in order to examine weather the interaction effects drastically change any of the relationships without the interaction effects.

### 2.3.3 Mediation analysis

Lastly in order to examine how the relationships between the stringency variables and the other variables are moderated by the other variables a mediation analysis was performed. A mediation analysis compares how a direct effect between the independent variable (IV) and a dependent variable (DV) changes when a third, mediator variable is introduced (MV). In particular it compares how the total effect of IV on DV is distributed across the direct effect (IV to DV) and the mediated effect (IV to MV to DV). The mediation analysis is able to determine weather there is a significant mediation effect, what proportion of the total effect it composes and weather it is a mediation or suppression effect. In the case when the direct effect and the mediation effect have the same sign, that means that the mediation effect strengthens the direct effect, while if their signs are opposite, it means that the mediation effect is suppressing the direct effect.

For each of the selected stringency metrics (1 for each cluster) 2 mediation analysis were performed. In both it was an independent predictor, in one trust was the mediator, while the mental well being was the dependent variable and in the other their roles were reversed (trust was the dependent variable and mental well being a mediator). In order to strengthen the result, each mediation analysis was run as a non-parametric bootstrap and created confidence intervals for each part of the results.

## 2.4 Predictive models

In order to examine weather the future values of trust in government and mental well being can be predicted from the past values, predictive models were built.The flattened data was used as training and testing data. The models goal was to predict a values of a dependent variable (either mental well-being or trust in government) at time step N based on the values of all variables (including the dependent variables) at time steps N-1 to N-D where D is the depth of a sample. The model is supposed to show how informative past values of variables are in predicting future values and weather the depth of the sample matters for predictive proposes.

#### 2.4.1 The model

The model used for the task was an Long Short Term Memory Network (LSTM) with variable length input. An LSTM is a type of a recurrent neural network (RNN) where unlike in a feed forward neural network, the neurons are also connected with other neurons in the same layer. This allows for the creation of feedback connections and loops, which in turn allows the network to gain extra information from the temporal structure of the data provided, which makes it useful for tasks such as speech and handwriting recognition, as well as time series forecasting. A LSTM is a special type of an RNN where instead of neurons, the network is composed of more complex LSTM cells, which help it deal with relations within the data that are separated by a long distance, to which the LSTM cells are resilient. An LSTM is trained through a combination of gradient descent algorithm an a back propagation through time algorithms, which "unfold" the network into a feed forward neural network, to which a standard back propagation can be applied.

#### 2.4.2 The data

The data used by the model was created by transforming each row from the flattened data sets into tensors, where each column represented a single variable and each row represented a different time steps (N-1 to N-D) of the same participant. The correct predictions were simply the values of the dependent variables at time steps N. The data structure used to accommodate for the different lengths of tensors was the ragged tensor from Tensorflow library. On top of that all the variables (except for the correct predictions in order to make the results more interpretable) were standardised in order to increase the accuracy of the model adn to prevent variables with larger values from overpowering the other variables.

#### 2.4.3 Optimisation

The model will be optimised by using an Adam optimiser in order to minimise the Mean absolute error (MAE) of the predictions.

Since the performance of the trained model highly depends on its hyperparameters, in order to achieve best results hyperparameter tuning was performed. Because of that a hyperparameter tuner was used in order to choose the topology of the network. The options out of which it has been choosing has been the size of one LSTM layer (from 25 to 200 with intervals of 25), weather to include and size of another layer of LSTM units (from 25 to 200 LSTM units with interval of 200) and the learning rate of the Adam optimiser (0.01, 0.001 or 0.0001). The hyperparameter optimiser used for the task has been the Hyperband optimiser implemented in the Keras library.

Due to the fact that the problems of predicting mental well being and trust in government are very similar, only one hyperparameter optimisation will be performed. Afterwards two LSTM models with the same topology will be trained separately to predict the different dependent variables. After performing the hyperparemeter optimisation the following network design was chosen. The network starts with the input layer, followed by 2 LSTM layers with 100 and 125 LSTM units respectively. Both of them use L2 regularizers with the weight of 0.001. Finally the network ends with a dense layer with 1 neuron which reports the value. The network uses an Adam optimiser with the learning rate of 0.001. During the hyperparemeter optimisation such a topology resulted in the lowest validation loss (0.290995) . In the next steps such a network will be used.

#### 2.4.4 Anti-overfitting and reproducibility measures

Since machine learning models often suffer from overfitting multiple measures have been taken in order to detect it and minimise its impact. First of all, at the beginning of the analysis 10% of the data has been set away in a "lock-box" and wasn't used at all during the training of the LSTM network. At the end it will be used in order to evaluate the model. By comparing how well it does on the validation data and the lock-box data it will be possible to establish to what degree the model is overfitting.

One of the causes of overfitting is the fact that during training, very high magnitudes of weights may emerge. This may be useful it fitting the model to the training data but it is makes it very sensitive to small changes in data (which may be caused by noise). Because of that it may cause overfitting. In order to prevent that L2 layer weight regularizers were introduced to both layers with the regularisation factor of 0.001. During optimisation they introduce a penalty term for high magnitudes of weights, which incentivises the optimiser to use smaller weights thus reducing the risk of high sensitivity to noise and thus overfitting.

On top of that, during the entire process all the stochastic elements in the process were seeded with seed=1. That was done in order to increase the reproducibility of the study, by making sure all the random processes can be replicated.

#### 2.4.5 Model evaluation

After fitting the hyperparameters and parameters the model will be evaluated. The metric used will be mean absolute error (MAE), which was selected in order to make the results more interpretable. The values of MAE will be compared between the LSTM model and an persistence model. The persistence model is often used as a baseline for time series prediction tasks. When asked to predict a value of a variable at time step N it will report the value of that variable at time step N-1. The models will be compared in order to examine weather the LSTM models has a significantly better predictive ability that the predictive ability that the persistence model. The two models will be compared across different input lengths in order to evaluate weather providing the LSTM model with more data will further improve its predictive ability and increase its advantage over the persistence model. Finally the results will be compared to the results obtained on the data from the lock box in order to examine weather significant overfitting has occurred.

# 3 Results

## 3.1 Statistical analysis

### 3.1.1 Selecting stringency metrics

In order to evaluate relationships between the stringency metrics a correlation plot and a dendrogram was created.

The correlation plot (3.1) depicts the correlations between all of the stringency variables (positive correlations are blue, while negative are red). By looking at the plot it can be identified that there seem to be 3 clusters. One cluster includes the monthly difference in stringency, number of changes in a month, sum of absolute changes in a month and standard deviation of stringency over a month, all of which are positively correlated. All those variables are different measures of the variability of the stringency over a month. Second cluster includes the mean stringency over a month, mean stringency over a week and value of stringency at a time of measurement, all of which are positively correlated. All of those variables are related to absolute values of stringency instead of its variability, because of which it makes sense that they are correlated. The last cluster contains number of stringency changes in a week, standard deviation of stringency over a week, sum of absolute changes over a week and difference of stringency over a week. The first 3 variables are positively correlated with each other and negatively correlated with the 4th variable, which still means that they are all highly related. All of them are different measures of variability of stringency over a week.

In order to further confirm the clustering based on visual analysis of the correlation plot, further methods were used. In order to do that ascendant hierarchical clustering of variables was performed in order to create clusters of most similar variables. Dendrogram in the appendix (A.3) is the dendrogram representing the hierarchical clustering. The lower the "height" at which a cluster is created the more strongly related the variables are. On the dendrogram it is further possible to see the same clustering as the one deduced from the correlation plot. Furthermore the stability plot in the appendix(A.4) further demonstrates that any partition of the variables in 3 or more sets is perfectly stable, further supporting the proposed clustering.

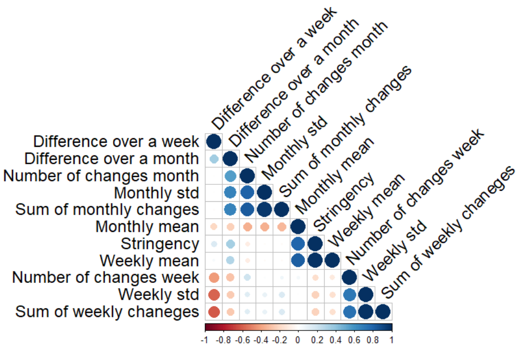


**Figure 3.1: Stringency variables correlation plot**

#### 3.1.2 Selecting stringency variables from clusters

In order to avoid issues connected to multicolinearity caused by including many highly correlated variables, only a single variable from each cluster has been selected. In order to do that individual predictive ability of each variable in a cluster, as well as the first PCA component was tested and compared. Afterwards the variable from each cluster with the highest predictive ability (measured by $R^2$) was selected. Due to the fact that the variables are supposed to predict both the mental well being and trust in government, in cases when different variables will be the best predictors for those dependent variables, a multiple of $R^2$ values will be used for evaluation. The summary of the results can be found in table A.1 in the appendix. The selected variables are followed by a *.

In the absolute value of stringency cluster it can be seen that the stringency is the best predictor of mental well being ($R^2 = 0.00378$), while the monthly mean is the best predictor of trust in government ($R^2 = 0.004727$). However due to the fact that stringency also performs relatively well for trust ($R^2 = 0.003699$), while monthly mean doesn't perform well for mental well being ($R^2 = 0.0001315$), makes stringency the variable used to represent the entire cluster. In the weekly variation cluster, the weekly number of changes of stringency is the best predictor for both mental well being ($R^2 = 0.00331$) and trust in government ($R^2 = 0.003405$), which makes it the variable representing the entire cluster. For the monthly variation cluster, mental well being is best predicted by the difference over a month ($R^2 = 0.01775$) while trust is best predicted by the number of changes over a month ($R^2 = 0.0006819$). Due to the fact that number of changes over a month performs relatively better for the mental well being ($R^2 = 0.005905$) than change over a month does for trust ($R^2 = 0.000104$) it is selected as a variable representing the cluster.

#### 3.1.3 Analysing linear relationships

In the end to look at all the variables together, four linear regression models were created and their coefficients were plotted. The ones for mental well being can be seen on figure 3.2 while the ones for trust in government can be seen in figure 3.3. For both dependent variables two models were created, one with and one without the interaction effects (the models with the interaction effects include additional coefficients in front of the multiplication of two interacting terms, for example trust and stringency). Additionally the tables presenting the full results of the regressions are included in the appendix (A.3 and A.4 respectively). All the independent variables were standardised before the linear regressions in order to make the results visible, despite different scales of the variables.

Based on the 3.2 it can be seen that trust in government has the highest positive coefficient. Since the model is predicting mental well being it means that people who trust the government more tend to experience higher levels of mental well being. The opposite can be observed for stringency, as its coefficient is negative. That means that people living in areas with higher stringency of lockdowns tend to experience worse mental well being. The weekly and monthly number o changes seem to have opposite effects on mental well being. Due to the positive coefficient the higher weekly number of changes is a predictor of higher levels of mental well being. On the other hand negative coefficient indicates that as the number of changes of stringency in a month increases the mental well being decreases. Moreover there appear to be negative interaction effects for the interactions between trust and stringency, and trust and weekly number of changes, while the interaction between the trust and monthly number of changes seems to be positive (all are statistically significant). However none of the interaction effects drastically influences the effects of individual variables (as can be seen by comparing the coefficients of the models with and without interactions).

Based on the 3.3 it can be seen that mental well being has the highest positive coefficient. Since the model is predicting trust in government it means that people experience higher levels of mental well being also tend to be more trusting of the government. Smaller but also positive coefficients can be observed for all 3 stringency variables. That means that people in areas with more stringent lockdowns as well as people in areas where the number of stringency changes in a previous week and month has been higher tend to be more trusting toward the government. Moreover there appear to be negative interaction effects for the interactions between mental well being and stringency, and mental well being and weekly number of changes, while the interaction between the mental well being and monthly number of changes seems to be positive (but not statistically significant as can be seen by its p-value in A.4).

#### 3.1.4 Mediation analysis

For all the selected stringency values 2 mediation analysis were performed. In one mental well being was the mediator and trust was the dependent variable and vice versa for the second one. For all 6 cases the mediation effect was found to be significant. The values for the proportion of effect can be seen in figure 3.4 (precise results can be seen in on A.2). The magnitude of the proportion show how influential on the total effect the mediation effect was, while the sign of the proportion show weather the effect was mediating (positive proportion) or suppressing (negative proportion). First it can be observed that the mediation proportions when stringency was the independent variable are for both dependent variables around 17%. That means that approximately 17% of the effect between the IV and DV was passed through the MV and that it was directed the same way. For example if one examines the effect of stringency on mental well being, from linear regression we know that the direct effect of increasing stringency is a decrease of mental well being. The mediated effect of an increase in stringency is the increase in trust in government, which causes an increase in a level of mental well being. It can be observed that the direct and mediated effects are opposite, hence the negative proportion. A similar effect can be observed for the monthly variation, while the opposite is true for weekly variation.

### 3.2 Machine learning predictions

In order to examine weather there are patterns in individual trajectories of peoples mental well being and trust in government, machine learning models were trained and tested.

#### 3.2.1 Training

After some trial training it was determined that the performance of the model on the validation data stops increasing after approximately 60 epochs of training. Because of that the final models were trained for 60 epochs. Graphs A.6 and A.5 in the appendix represent the training and validation losses of the training of the mental well being and trust models respectively. The final validation losses are 0.2696 and 0.3149 respectively (more in table 3.1).

#### 3.2.2 Model evaluation - Mental well being

The model is trying to predict the value of the mental health index (index combining responses about different emotions) of given participant at step N, while being provided with values of mental well being index, trust in government, stringency and weekly and monthly number of changes from time steps 1 to N-1. First the trained models performance was compared to the persistence model on the full test set. The MAE of the LSTM model was 0.2685 while persistence model achieved MAE of 0.3233, thus showing that the performance of the LSTM model was superior. Next the performance of both models was compared on different input lengths in order to determine weather the LSTM models performance increases when a longer time series of data is supplied to it. The results can be seen on graph 3.5. The graph shows that while at depth 2 the performance of models is not significantly different, it very quickly diverges. For all depths higher than 2 the LSTM model performs significantly better than the persistence model. More-

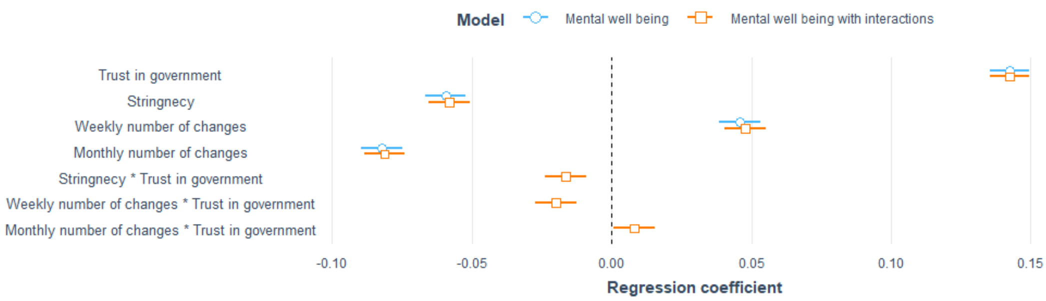


**Figure 3.2: Coefficients of the models predicting mental well being**

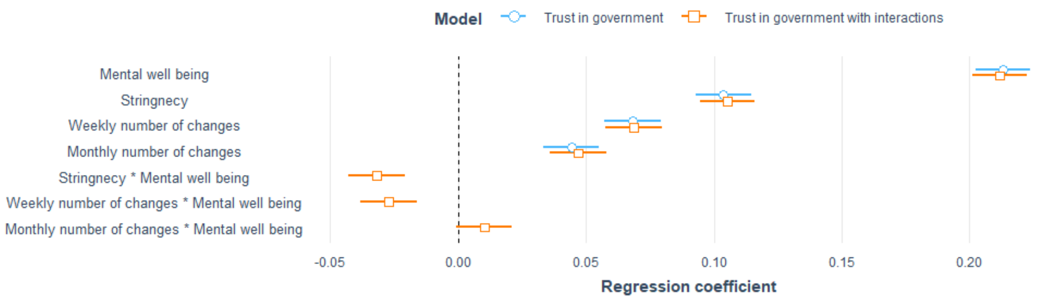


**Figure 3.3: Coefficients of the models predicting trust in government**

over its performance is strictly increasing with the exception of depth 9. Finally the performance was tested on the data stored in the lock box in order to confirm that the results were not over fitted. The MAE values from the entire lock box set and the test set can be seen in table 3.1. It can be seen that while the performance on the lock box data is slightly worse than on the test data, it is still very similar. Since the model is bale to perform well on data witch it didn't encounter before that means that it is not overfitted and is generalisable. As the LSTM model was able to perform better than the persistence model, that indicates that in fact there are patterns in individual trajectories of mental well being.

### 3.2.3 Model evaluation - Mental trust in government

The model is trying to predict the value of the participants response to a question about trust in government at step N, while being provided with values of mental well being index, trust in government, stringency and weekly and monthly number of changes from time steps 1 to N-1. First the trained models performance was compared to the persistence model on the full test set. The MAE of the LSTM model was 0.3141 while persistence model achieved MAE of 0.3307, thus showing that the performance of the LSTM model was slightly superior. Next the performance of both models was compared on different input lengths in order to determine weather the LSTM models performance increases when a longer time series of data is supplied to it. The results can be seen on graph 3.6. The graph shows that while at depths smaller than 5 the performance of models is not significantly different, it later diverges. For all depths higher than 5 the LSTM model performs significantly better than the persistence model. Moreover its performance is strictly increasing with the exception of depth 10. Finally the performance was tested on the data stored in the lock box in order to confirm that the results were not overfitted. The MAE values from the entire lock box set and the test set can be seen in table 3.1. It can be seen that the performance of the model on the lock box data is slightly better than that on the test data. The difference is

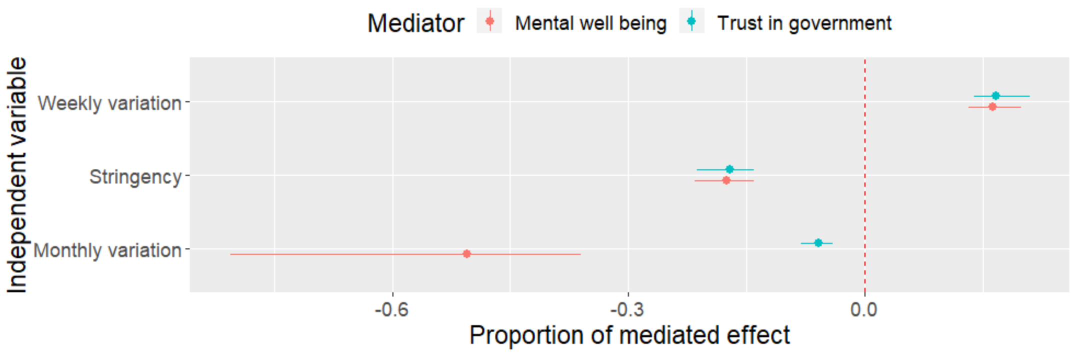


**Figure 3.4: Proportion of mediated effect**

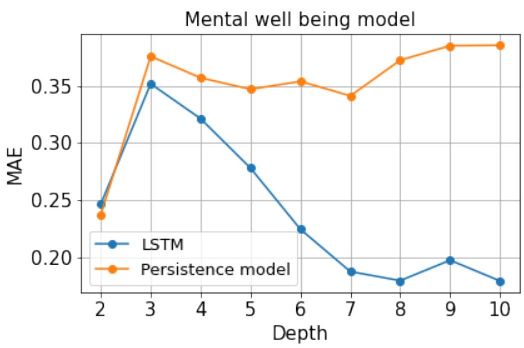


**Figure 3.5: Mean Absolute Error of the LSTM and persistence models predicting mental well being over different input lengths**

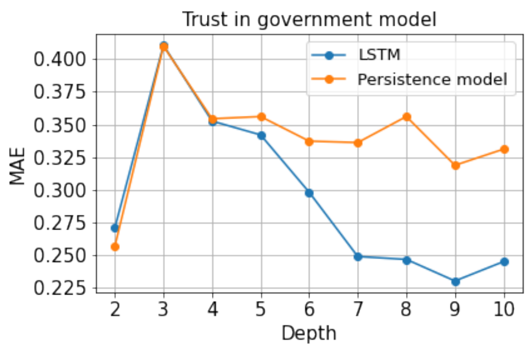


**Figure 3.6: Mean Absolute Error of the LSTM and persistence models predicting trust in government over different input lengths**

negligible and it shows that the model is able to perform just as well on the data it hadn't seen before. Since the model is bale to perform well on data witch it didn't encounter before that means that it is not overfitted and is generalisable. As the LSTM model was able to perform better than the persistence model, that indicates that in fact there are patterns in individual trajectories of trust in government.

# 4 Discussion

Next, linear regression was performed in order to examine the relations between all of the variables. As expected, it was found that participants with higher levels of trust in government generally exhibited higher levels of mental well being. This results further confirms multiple studies mentioned beforehand. As expected, higher levels of the stringency index caused a decrease in mental well being, which is in agreement with past findings that lockdowns tends to create a decrease in well being. Surprisingly, a higher number of changes of stringency during a week contributed positively towards ones mental well being, while the monthly number of changes contributed negatively to it. The interaction effects between the trust in government and all of the stringency metrics, were significant, however none of them significantly changed the individual effects of each variable.

A linear regression predicting trust in government showed that mental well being positively contributes to trust in government. That further shows a two way positive interaction between the variables. Surprisingly, all of the stringency variables were also positively contributing towards the trust

| Dependent variable | Model | Test MAE | Lock box MAE |
|---|---|---|---|
| Mental well being | LSTM | 0.2685 | 0.2794 |
| Mental well being | Persistence | 0.3233 | 0.3303 |
| Trust in government | LSTM | 0.3141 | 0.3098 |
| Trust in government | Persistence | 0.3307 | 0.3288 |

**Table 3.1: Mean absolute errors of the LSTM and persistence models on all depths**

in government. This means that a higher level of stringency at a time, as well as higher weekly and monthly number of changes were positively contributing to trust in government. The increase of trust caused by the stringency confirms the findings from the initial stages of the pandemic in which increases in trust were observed. The results are likely similar due to the fact that a large portion of data use din this study, also came from the early stages of the pandemic (approximately 75% came from up to 30 May 2020). Moreover the positive effect of the frequency of changes can be explained by action bias (Patt and Zeckhauser (2000)), which means that people prefer action over inaction even in situations where action can be harmful. In a stressful situation, harder lockdowns and more changes can be interpreted as government actively dealing with the pandemic, which may induce trust. Furthermore the results may be affected by the fact that most of the data has been collected in the early stage of the pandemic. In this regression the interaction effect between mental well being and monthly number of changes was not statistically significant. Other interactions, while significant, also didn't change the nature of the relationship between the variables.

Both linear regressions achieved relatively small $R^2$ values of approximately 4.5% and 3.9%. This means that while the factors examined are significant predictors, they only account for a small part of the variation in mental well being and trust in government.

Next mediation analysis was performed on the resulting stringency variables, mental well being and trust in government, such that the stringency metrics were the predictors while the other variables were either a mediator or the dependent variable. It was found that in all cases a small but statistically significant proportion of the effect between the independent and the dependent variable was mediated by the mediator. In the case of stringency and monthly variation it was shown that the effect of introducing either mental well being or trust in government was creating a suppressing effect, while in the case of weekly variation the effect was mediating.

Finally predictive models were used in order to examine weather the future values of trust and well being can be predicted based on past data. The trained LSTM model was able to achieve significantly better MAE values that the persistence model which was used as a baseline comparison. This shows that the data can be predicted successfully to a high degree, since MAE levels of around 0.27 for mental well being and 0.31 for trust in government are quite small compared to the fact that the range of possible values is 4 (-2 to 2 for mental well being index and 1 to 5 for trust in government).

The higher MAE values for trust in government can be explained by a variety of factors. First, it may be the case that trust in government is simply more volatile and less predictable than mental well being. Second, the fact that the hyperparameter training was performed while predicting mental well being may have caused the architecture of the network to be better optimised towards predicting it. However due to the mirror structure of the problems this seems unlikely. Lastly the effect may be caused by the fact that trust in government had a more discrete scale, which meant that each mistake would result in a higher error (thus increasing MAE).

Moreover it was shown that providing the LSTM model with more time steps increases the quality of the predictions. In the meantime there was no effect on the persistence model. That shows that not only can those variables be reliably predicted, but that providing more data to the algorithms increases prediction quality.

An interesting anomaly that can be seen on both graphs is that for depth 2 the performance of both models is significantly better than for depth 3. This is especially curious for the persistence model, since it shouldn't be at all affected by more data. I believe that the anomaly can be explained by the method by which the data sets were initially connected. Among data points with depth 2, in many of them the first one consists of the baseline survey, while the final one (the one being predicted) is the first wave to which a person responded. Since the person had to respond to the survey sometime between the waves, it means that the time between the baseline response and the first wave response has to be smaller than between two wave responses. Assuming that a person is more similar to herself in a more recent past, that would explain why those data points were predicted more accurately. Since its only the last data point that is being predicted, in all cases outside depth 2 the distance between the last two responses is always the same as between waves.

## 4.1 Limitations

The results of the study could have been affected by a number of factors, some stemming from the problems with the data, some stemming from the methodology not accounting for something.

The results may not generalise to the entire population due to the fact that people who take part in surveys such as PsyCorona may have certain characteristics that are different than the general population. Among others they may be more trusting in science and may be more comfortable sharing their information than the general population. Due to the fact that all the data was gather from such people, the results regarding for example higher stringency increasing trust in government may not generalise. Moreover while approximately half of the data was gathered from paid panels which were ensured to be demographically representative, the other half of the data, coming from volunteers was not demographically representative. Further complications may stem from the fact that the PsyCorona data is composed fully of self-reported data. While there is no much that could be done to avoid that, this still may introduce some bias towards the results.

Another problem connected to the data is the fact that the vast majority of the data was collected in the early stages of the pandemic (75% were collected up to 30th May 2020). This may cause problems due to the fact that interactions between different variables may change over time. For example, while at the beginning a higher number of changes to stringency may be encouraging trust, as people feel like the government is doing something, later they may interpret it as the government not being certain what is the right policy. The fact that the vast majority of the data comes from the early stages of the pandemic may bias the results towards the way people reacted back then. That problem comes not only from the distribution of data in time, but also from the fact that the study didn't examine how the dynamics between the variables change across different waves.

Next problem which may have decreased the performance of the LSTM models was the fact that the time between different waves was not constant. While the first 11 waves were performed weekly, afterwards the measurements became monthly.

Next thing not examined in the study was the fact that the interactions between the variables could be different in different countries, for reasons connected to culture, economics, relation between the government and the population before the pandemic and many others. For example if the government had a history of oppressive policies, the lockdowns may be interpreted by the population as an attack on them instead of a preventive measure, thus resulting in the decrease in the trust instead of an increase). The study examined did not distinguish between different countries, which made it unable to take those differences into a account and moreover it biased the results to be similar to the countries which provided most responses.

Next problem stems from the fact that there is a very strong relation between the strictness of lockdowns and the severity of COVID-19 in an area. Since the study doesn't account for the severity of COVID-19, the effects of it may have been misinterpreted as results of strict lockdowns. For example, the effects of lockdowns on mental well being may be much smaller if the effects of COVID-19 are accounted for separately. The fact that variables such as number of cases or deaths were not included may make the results at least somewhat questionable.

The study used an index as an operationalization of mental well being. However a lot more interesting information could be gained by looking each of the affect variables individually, as it is likely that each interacts differently with other variables. For example it may be the case the anxiety is affected more strongly by the lack of trust in government than depression is.

Another factor that could possibly have influenced the results was the method by which the data sets were connected. In order to do that, dates at which responses were made had to be estimated. It was relatively easy for the wave responses, since dates at which the questionnaires were sent was known. However for the baseline responses no date was provided. The estimations were chosen to be the date between first wave in which the person responded and the wave before. First of all this caused possible problems due to the fact that the values of stringency variables estimated for that date were likely to not be exactly accurate. Moreover since the distance between the baseline and first wave response was smaller than between wave responses, this caused the set of data of depth 2 to be easier to predict than the other sets, which caused the anomaly in predictive models discussed in sections 2.4 and 3.2 .

Lastly, the statistical analysis in no way accounted for the demographic differences in data. It did not examine how the results are dependent on factors such as education, age or gender.

### 4.2 Future research

Future research could focus on the aspects of the results that were not accounted for by this study. Among others it could deeply examine how the relation ship between stringency, trust and mental well being changed over the course of the pandemic. Such a research would be able to reveal weather the effects that caused the increase in trust at the beginning of the pandemic stop influencing the results so strongly and it would be able to examine what other factors starts playing a larger role over time.

Moreover it could examine how the they differed across different regions and demographic groups. Such a study would be able to show how differences between cultures, attitudes toward governments, political affiliations in different countries and other factors affect how people trust and well being are affected by stringency. As there is a clear variation within and between countries, examining what factors contribute to those differences could yield informative results.

## References

Gilles, I., Bangerter, A., Clémence, A., Green, E. G., Krings, F., Staerklé, C., and Wagner-Egger, P. (2011). Trust in medical organizations predicts pandemic (h1n1) 2009 vaccination behavior and perceived efficacy of protection measures in the swiss public. *European journal of epidemiology*, 26(3):203–210.

Goldfinch, S., Taplin, R., and Gauld, R. (2021). Trust in government increased during the covid-19 pandemic in australia and new zealand. *Australian Journal of Public Administration*.

Gustavsen, A., Røiseland, A., and Pierre, J. (2014). Procedure or performance? assessing citizen's attitudes toward legitimacy in swedish and norwegian local government. *Urban Research & Practice*, 7(2):200–212.

Hale, T., Petherick, A., Phillips, T., and Webster, S. (2020). Variation in government responses to covid-19. *Blavatnik school of government working paper*, 31:2020–11.

Harring, N., Jagers, S. C., and Löfgren, Å. (2021). Covid-19: large-scale collective action, government intervention, and the importance of trust. *World Development*, 138:105236.

Kontoangelos, K., Economou, M., and Papageorgiou, C. (2020). Mental health effects of covid-19 pandemia: a review of clinical and psychological traits. *Psychiatry investigation*, 17(6):491.

Kreienkamp, J., Agostini, M., Krause, J., Leander, N. P., Collaboration, P., et al. (2020). Psycorona: A world of reactions to covid-19. *APS Observer*, 33(9).

Lim, V. W., Lim, R. L., Tan, Y. R., Soh, A. S., Tan, M. X., Othman, N. B., Dickens, S. B., Thein, T.-L., Lwin, M. O., Ong, R. T.-H., et al. (2021). Government trust, perceptions of covid-19 and behaviour change: cohort surveys, singapore. *Bulletin of the World Health Organization*, 99(2):92.

O'Hara, L., Abdul Rahim, H., and Shi, Z. (2020). Gender and trust in government modify the association between mental health and stringency of public health measures to reduce covid-19.

Patt, A. and Zeckhauser, R. (2000). Action bias and environmental decisions. *Journal of Risk and Uncertainty*, 21(1):45–72.

Prati, G. and Mancini, A. (2021). The psychological impact of covid-19 pandemic lockdowns: A review and meta-analysis of longitudinal studies and natural experiments.

Rajkumar, R. P. (2020). Covid-19 and mental health: A review of the existing literature. *Asian journal of psychiatry*, 52:102066.

Saechang, O., Yu, J., and Li, Y. (2021). Public trust and policy compliance during the covid-19 pandemic: The role of professional trust. In *Healthcare*, volume 9, page 151. Multidisciplinary Digital Publishing Institute.

Sibley, C. G., Greaves, L. M., Satherley, N., Wilson, M. S., Overall, N. C., Lee, C. H., Milojev, P., Bulbulia, J., Osborne, D., Milfont, T. L., et al. (2020). Effects of the covid-19 pandemic and nationwide lockdown on trust, attitudes toward government, and well-being. *American Psychologist*.

Thoresen, S., Blix, I., Wentzel-Larsen, T., and Birkeland, M. S. (2021). Trust and social relationships in times of the covid-19 pandemic. *European Journal of Psychotraumatology*, 12(sup1):1866418.

Vindegaard, N. and Benros, M. E. (2020). Covid-19 pandemic and mental health consequences: Systematic review of the current evidence. *Brain, behavior, and immunity*, 89:531–542.

# A Appendix

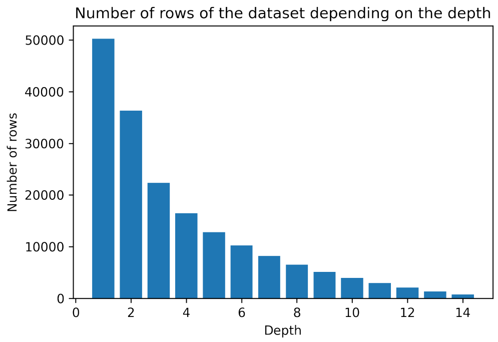


**Figure A.1: Number of rows in the dataset by depth**

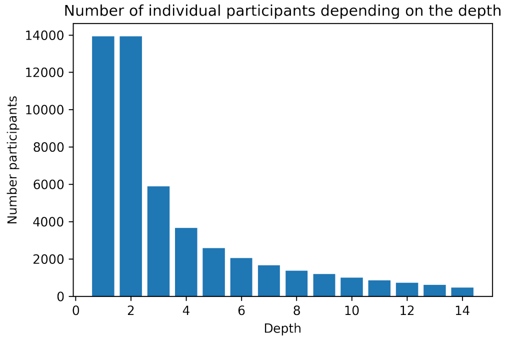


**Figure A.2: Number of participants in the dataset by depth**

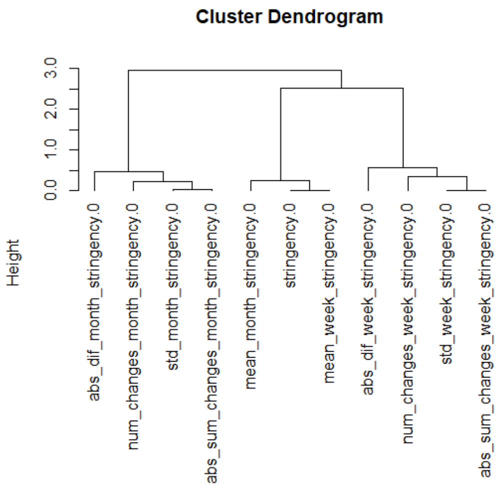


**Figure A.3: Stringency variables dendrogram**

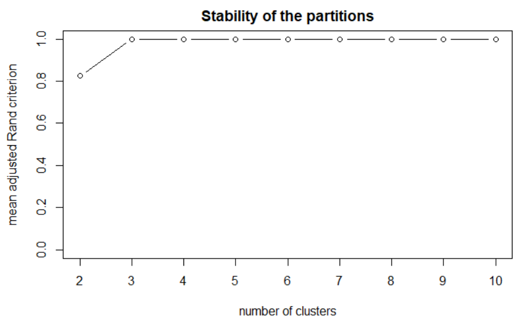


**Figure A.4: Stability of stringency variables clustering**

| Independent variable | Mental well being $R^2$ | Trust in government $R^2$ |
|---|---|---|
| **Stringency*** | **0.00378** | 0.003699 |
| Weekly mean | 0.003327 | 0.004046 |
| Monthly mean | 0.0001315 | **0.004727** |
| PCA | 0.001494 | 0.004511 |
| Weekly standard deviation | 0.001354 | 0.001561 |
| **Weekly number of changes*** | **0.00331** | **0.003405** |
| Weekly sum of absolute changes | 0.001647 | 0.001525 |
| Change over a week | 0.001761 | 0.0004715 |
| PCA | 0.002479 | 0.002077 |
| Monthly standard deviation | 0.005491 | 0.0003682 |
| **Monthly number of changes*** | 0.005905 | **0.0006819** |
| Monthly sum of absolute changes | 00.006173 | 0.0005713 |
| Change over a month | **0.01775** | 0.000104 |
| PCA | 0.01205 | 0.0003032 |

**Table A.1: Individual predictive ability of stringency variables**

| Independent variable | Dependent variable | Mediator | Proportion of mediated effect |
|---|---|---|---|
| Stringency | Mental well-being | Trust in government | -0.17 |
| Stringency | Trust in government | Mental well-being | -0.17 |
| Weekly variation | Mental well-being | Trust in government | 0.17 |
| Weekly variation | Trust in government | Mental well-being | 0.16 |
| Monthly variation | Mental well-being | Trust in government | -0.06 |
| Monthly variation | Trust in government | Mental well-being | -0.50 |

**Table A.2: Results of mediation analysis on selected stringency variables**

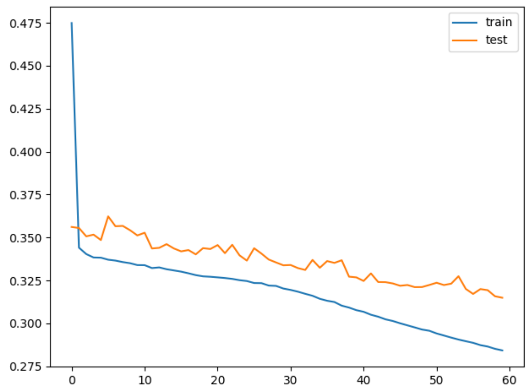


**Figure A.5: Training and validation loss of the Trust model over training**

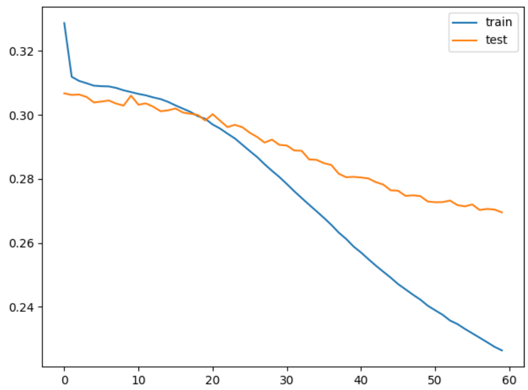


**Figure A.6: Training and validation loss of the mental well being model over training**

| Coefficient | Estimate | Std. Error | p-value |
|---|---|---|---|
| Intercept | 0.216540 | 0.003627 | <2e-16 |
| Trust in government | 0.142590 | 0.003629 | <2e-16 |
| Absolute stringency | -0.058136 | 0.003693 | <2e-16 |
| Weekly variation | 0.047962 | 0.003766 | <2e-16 |
| Monthly variation | -0.081304 | 0.003699 | <2e-16 |
| Trust and Absolute stringency | -0.016353 | 0.003737 | 1.21e-05 |
| Trust and Weekly variation | -0.019941 | 0.003744 | 1.01e-07 |
| Trust and Monthly variation | 0.008040 | 0.003773 | 0.0331 |

**Table A.3: Results of linear regression, predicting mental well being.** $R^2 = 0.04503$

| Coefficient | Estimate | Std. Error | p-value |
|---|---|---|---|
| Intercept | 2.884761 | 0.005426 | <2e-16 |
| Mental well being | 0.211916 | 0.005429 | <2e-16 |
| Absolute stringency | 0.105285 | 0.005492 | <2e-16 |
| Weekly variation | 0.068744 | 0.005616 | <2e-16 |
| Monthly variation | 0.046980 | 0.005634 | <2e-16 |
| Mental well being and Absolute stringency | -0.031833 | 0.005654 | 1.81e-08 |
| Mental well being and Weekly variation | -0.027294 | 0.005682 | 1.56e-06 |
| Mental well being and Monthly variation | 0.010203 | 0.005537 | 0.0654 |

**Table A.4: Results of linear regression, predicting trust in government.** $R^2 = 0.03939$