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Differences in government responses during the COVID-19 pandemic: A cluster analysis

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List of Abbreviations

ANOVA	Analysis of Variance
CCI	Containment and Closure Index
ECDC	European Centre for Disease Prevention and Control
ERI	Economic Response Index
GDP	Gross Domestic Product
HSI	Health System Index
IMF	International Monetary Fund
KML	K-means for longitudinal data
NGO	Non-governmental organisation
NIE	New Institutional Economics
NTI	Nuclear Threat Initiative
OxCGRT	Oxford COVID-19 Government Response Tracker
RSF	Reporters Without Borders
WHO	World Health Organization
WVS	World Values Survey

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1. Introduction

In 2020, the global economy contracted by an estimated 3.5 percent, an unexpected sharp deviation from previous forecasts. Similarly, world trade volumes declined by 9.6 percentage points compared with 2019 due to severe direct negative supply and indirect negative demand shocks (Canuto 2020: 3; IMF 2021: 4f.; Tooze 2021: 112–125). This was triggered by an easily transmissible novel coronavirus (SARS-CoV-2) causing the infectious disease COVID-19, which first appeared in the Chinese city of Wuhan in December 2019. Shortly thereafter, numerous countries reported cases of infection (WHO 2022b). On March 11, 2020, the World Health Organization (WHO) declared the disease a pandemic and advised countries to adopt "a whole-of-government, whole-of-society approach" (ibid.).

Various countries followed the WHO's recommendation and implemented regulations severely restricting people's daily lives: workplaces were closed, public transportation was reduced, border crossing was restricted or entirely prohibited, and facial coverings were prescribed. What all governments had in common was that they faced a trade-off: On the one hand, they wanted to contain the spread of the virus and prevent deaths. On the other hand, by imposing measures on the population, governments restricted people's freedom and reduced economic prosperity (Chen et al. 2021: 2). Since the assessment of the trade-off varied and a wide range of response options were available, the governments' responses ultimately fell far apart. For example, while Swedish decision-makers primarily made appeals to the people to protect themselves (Eversmann 2021: 116), the Chinese government opted for strict lockdowns of the affected regions and increased surveillance (Lu et al. 2021: 4). Shortly after the differences in government stringency became apparent, researchers began to seek reasons for these variations. Explanatory variables included previous experience with infectious diseases (Capano et al. 2020), proximity to the next elections (Pulejo/Querubín 2020), whether the incumbent national health minister had a medical background (Toshkov et al. 2022), cognitive biases or a tendency towards panic among decision-makers (Maor/Howlett 2020), as well as social (Chen et al. 2021) and legal culture (Czetwertyński/Sukiennik 2021).

This thesis aims to complement existing research findings by gaining further insight into the different responses of governments during the most acute phase of the pandemic, which terminated with the vaccination of the first 0.01% of the population of the United States on December 13, 2020. This quantitative study covers about 180 countries. Among these countries, a clustering algorithm seeks patterns in which certain groups of countries respond with similar stringency and roughly uniformly over time (both in relation to coronavirus exposure). The severity of the measures and the type of government response measures a country's stringency. Using the Oxford COVID-19 Government Response Tracker (OxCGRT) database (Hale et al. 2021), differentiations are made between containment and closure measures, economic responses, and health system responses.

K-means cluster analyses are conducted, partitioning countries into four to six groups, depending on the type of government response. Following New Institutional Economics (NIE) and Williamson's typology, it is then assumed that institutional factors can partially explain these patterns. According to NIE economists, individuals are constrained in their actions by an institutional environment that varies across countries (Czetwertyński/Sukiennik 2021: 572; North 1991: 108f.). Consequently, differences in institutions should elucidate some of the variations in government responses. These considerations culminate in the following research question: *Can differences in government responses to the COVID-19 pandemic be explained by institutional factors?*

Section 2 below provides an overview of the NIE perspective and its applicability to government responses during the COVID-19 pandemic. The following two sections are devoted to the two steps required to answer the research question: Section 3 first identifies groups of countries that responded similarly to the pandemic outbreak. It details the clustering method, the data, and the cluster analysis results. Next, institutional differences between the clusters are examined through an analysis of variance (ANOVA). Section 4 describes the variables selected and the results of the characterisation of the clusters. Finally, Section 5 summarises the main findings, responds to the research question, and identifies research gaps.

2. New Institutional Economics and the COVID-19 pandemic

Central to NIE is the assumption that "[l]egal, political, social, and economic institutions [...] have important effects on economic performance" (Joskow 2008: 5) since they constrain and incentivise human interactions. Institutions, defined as man-made rules and enforcement mechanisms that structure social action (North 1991: 97, 108f.; Nye 2008: 67), can be either formal, such as laws, property rights, and constitutions, or informal and originate in a society's culture, such as norms of behaviour, customs, and taboos (North 1991: 97; Przysada-Sukiennik 2021: 623). A functioning institutional system is essential for a society because it "improve[s] interpersonal relations, reduce[s] the uncertainty inherent in any exchange process, [and] limit[s] the transaction costs" (Czetwertyński/Sukiennik 2021: 573).

Government responses during the COVID-19 pandemic can unambiguously be classified as institutions: First, they are rules, such as the obligation to stay at home or the closure of national borders, combined with enforcement mechanisms, such as identity checks by police or fines (Terpstra et al. 2021). Second, (groups of) individuals, or more precisely, governments, decide on laws and regulations. Government responses can thus be considered man-made, formal institutions. Third, the policies influence people's behaviour by offering incentives, such as buying face masks when their use is recommended, and by imposing constraints, such as working from home when the number of people allowed working in the office is limited. Fourth, government responses also have an economic impact. For example, unemployment increases when retail workers are laid off because stores have to close.

A more precise classification of government responses is obtained using Williamson's well-known typology. Williamson distinguishes four interrelated levels of institutions. Informal institutions, traditions, and religion constitute the most basic level, the so-called "social embeddedness level" (Williamson 2000: 596). It is highly persistent – a perceptible change can be expected every 100 to 1000 years – and its constitution significantly impacts the second level, the institutional environment. This level includes formal institutions that have emerged in the last 10 to 100 years (ibid.: 596ff.), such as "the executive, legislative, judicial, and bureaucratic functions of government[, ...] the distribution of powers across different levels of government[, and t]he definition and enforcement of property rights" (ibid.: 598). Williamson defines the subsequent level as "the play of the game" (ibid.: 597), in which a collective of private actors or the government frequently, i.e., between 1 and 10 years, revises the institutions of governance, such as contracts and policies. These institutions affect the fourth institutional level, namely resource allocation. The neoclassical analysis focuses on this level, where prices and output continuously adjust (Pawłowski 2019: 89; Williamson 2000: 599f.).

Government responses represent institutions of governance, with governments rescinding regulations as soon as they declare the end of the COVID-19 pandemic (e.g., Joeres 2022; Mittelstaedt 2023). They are assumed to be influenced by first-, second-, and fourth-level institutions. The latter derives from the feedback loop included by Williamson in his typology that runs in reverse from the fourth to the first institutional level (2000: 596).[1]

A conundrum identified by Arrow as one of the main issues for NIE economists is "why economic institutions[2] emerged the way they did and not otherwise" (as cited in Williamson 2000: 596). An essential premise is the assumption that institutions evolve in a path-dependent manner (North 1991: 109). Consequently, there are rarely identical institutional systems, which lead to people or governments in different countries making different decisions that have distinct effects (Czetwertyński/Sukiennik 2021: 572ff.). This also applies to government responses during the COVID-19 pandemic.[3]

The NIE perspective is, therefore, of great value in elucidating variations in government responses. This became apparent in previous research identifying explanatory variables such as a country's culture (level 1), its legal system (level 2), or resource allocation in its healthcare

[1] While it is true that government responses are embedded in this feedback system and, therefore, may have significantly altered other institutions, this effect is not considered in this thesis. Instead, first-, second-, and fourth-level institutions are considered exogenous (Czetwertyński/Sukiennik 2021: 572; Legiędź 2021: 590).

[2] or, by extension, formal institutions (here: government responses)

[3] Furthermore, NIE economists emphasize that individuals are by no means perfectly informed. Instead, they assume that people are constrained by bounded rationality (Harvey 2015: 129f.; Williamson 2000: 600). This concept can be perfectly applied to the COVID-19 pandemic, where governments had to react swiftly despite great uncertainty about the extent of the pandemic and a lack of information about the consequences of their (non)actions. Taking this a step further, one could argue that even if the institutional systems of two countries were identical and the impact of the pandemic was similarly intense, policymakers would not have responded identically because of their "limited capacity to analyse highly complex situations" (Hodgson 2018: 50).

sector (level 4).[4] The final set of institutional variables used to characterise the clusters is detailed in Section 4.1. It includes first-level institutions, such as a society's cultural orientations, second-level institutions, such as democratic status, and fourth-level institutions, such as people's access to sanitation.

3. Cluster Analysis

This section describes the cluster analysis method and clarifies why the k-means algorithm is suitable for the analysis in this thesis (3.1). To enable replication of the research findings, the dataset used and its limitations are described (3.2). Furthermore, an insight into the steps of data preparation and k-means cluster analysis using the statistical software R is given (3.3 and 3.4).[5] Section 3 concludes with a description of the results of the cluster analyses (3.5).

3.1 The cluster analysis method and the k-means algorithm

The term 'cluster analysis' describes exploratory methods that aim to classify similar cases (here: countries) into groups, so-called 'clusters'. Critical to the unsupervised classification of cases into latent clusters are the input variables, i.e., the characteristics of the cases (here: government responses over time) (Attewell/Monaghan 2015: 197; Teuling et al. 2021: 2; Morissette/ Chartier 2013: 15; Schendera 2010: 8). As a result, each case is assigned a single identifying variable for the respective cluster. This summarises the information contained in the input variables and reduces the complexity of the dataset. Further statistical analysis aimed at characterising the clusters can then be more easily performed (Génolini et al. 2015: 3; Morissette/Chartier 2013: 15). The primary goal of cluster analyses is to achieve high intra-cluster homogeneity and high inter-cluster heterogeneity (Backhaus et al. 2018: 490).

Various clustering methods and algorithms exist, which differ in their operation and applicability and can lead to different results (Williams 2011: 189). A major distinction can be made between hierarchical and partitioning approaches. In hierarchical clustering, "the number of clusters is gradually increased or decreased until all objects form their own cluster [...] or all objects form a common cluster" (Stahlberg et al. 2022: 94, translation my own). Consequently, the clusters are nested (Attewell/Monaghan 2015: 203). In contrast, in partitioning algorithms, the researcher determines a target number of clusters *k*. Cases are then assigned to *k* disjoint clusters until the result is optimised (ibid.; Wentura/Pospeschill 2015: 165).

Due to the scope of this thesis, only one clustering algorithm can be applied. The method to be chosen has to process longitudinal data and identify common patterns among them (Teuling

[4] Chen et al. show, for example, that societies where individualistic values prevail were generally slower to respond to the spread of the virus than collectivist countries. The authors argue that governments, aware of the high value of personal freedom, feared social resistance in the first case (2021: 2, 5). Przysada-Sukiennik proves that the difference between the Swedish government's decision to rely mainly on appeals to the population and the Polish government's decision to impose an early lockdown is partly due to the different legal systems (2021: 631f.). Thoshkov et al. examine the impact of healthcare capacity as measured by the number of hospital beds. They find that governments responded rapidly when they expected the health sector to collapse, given its low capacity (2022: 1015, 1024).

[5] The complete R script is included with the thesis in digital form.

et al. 2021: 2). Partitioning approaches offer a promising implementation as they are more flexible and efficient for a large number of cases[6] (Backhaus et al. 2018: 565; Bruckers et al. 2016: 725; Williams 2011: 190). Among the partitioning approaches, k-means is the most popular method (McNulty 2020; Stahlberg et al. 2022: 96). Its version for longitudinal data (k-means for longitudinal data, KML) "scales well and converges to a solution relatively quickly" (Teuling et al. 2021: 8). Moreover, KML can easily handle sudden changes in variables over time (ibid.: 36), and its implementation in R is easily accessible (see 3.4). Although missing data may be an obstacle to the proper application of KML (ibid.), this drawback does not prevent its use in this thesis since all data are complete (see 3.3).

The operation of the k-means algorithm can be summarised as follows: In multidimensional space, *k* points are set as starting points and centres (centroids) of the initial clusters (Attewell/Monaghan 2015: 203).[7] All remaining observations are then assigned to a cluster. In an iterative process of two phases, the algorithm optimises the classification. In the first step, the so-called 'expectation phase', the centres of each cluster are determined (Génolini et al. 2013: 106). The centroid is the vector of mean values for each input variable (Schendera 2010: 117f.; Williams 2011: 181). In the subsequent maximisation phase, the most similar or closest cluster is identified for each observation (Génolini et al. 2013: 106) by calculating and comparing the distances (dissimilarities) between each observation and the centres of each cluster (Schendera 2010: 117f.).[8] The best-known measure, also used in this thesis, is Euclidean distance. It measures the length of the shortest straight line between two points in multidimensional space (Backhaus et al. 2018: 500).[9] Once the clusters are reassembled, their centres are calculated again, and the process starts from the beginning (Génolini et al. 2013: 106). This procedure – "calculating distances, assigning cases to centroids, finding mean points and shifting centroids" (Attewell/Monaghan 2015: 203) – is completed when the assignments to the clusters no longer change (Génolini et al. 2013: 106; Williams 2011: 181).

To obtain reliable results, this process is performed several times. Each time, a different number (*k*) of starting points can be specified, resulting in different numbers (*k*) of clusters. To find the optimal *k*, various internal clustering validation measures have been developed to evaluate the quality of each partition (Backhaus et al. 2018: 529; Liu et al. 2010: 911). Most of these objective quality criteria measure "how closely related the objects in a cluster are" (ibid.),

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6 The final dataset of this thesis contains six input variables (dimensions) for 175 countries at ten time points, thus a 1750 x 6 matrix.

7 Without further specification, these points are selected randomly, leading to different results when the analysis is performed several times. To avoid this problem, the starting point (seed) must be determined manually (Schendera 2010: 118; Williams 2011: 187).

8 Due to limited computational capacity and to reduce computational time, the algorithm does not compute the distance between every observation and *each* centroid. Instead, it uses a search heuristic (Williams 2011: 181).

9 The Euclidean distance is calculated as follows: $dE = \sqrt{\sum_i^k \left(c_i - x_i\right)^2}$ with "*c* [as] the cluster center, *x* [as] the case it is compared to, *i* [as] the dimension of *x* (or *c*) being compared[,] and *k* [as] the total number of dimensions" (Morissette/Chartier 2013: 16; emphasis in the original).

i.e., their compactness, and “how distinct [...] a cluster is from other clusters” (Liu et al. 2010: 912), i.e., their separation. Well-known measures include the Calinski-Harabasz index, which computes the ratio of covariance between clusters and covariance within clusters (Backhaus et al. 2018: 530), the Davies-Boulin index, or the root-mean-square standard deviation (Liu et al. 2010: 912; Vendramin et al. 2010: 220). Generally, there is no superior quality criterion (ibid.: 234), as all measures have their shortcomings (Liu et al. 2010: 916). Their applicability depends on various criteria, such as the research question and the data (Shim et al. 2005: 202). In this thesis, the best quality criterion that perfectly determines the optimal number of clusters cannot be identified. If, however, several criteria point to the same number of clusters, it is a solid indication of the quality of a partition (Génolini et al. 2015: 4).

Before proceeding with the data description, it is necessary to point out the limitations of cluster analyses. Most importantly, the cluster analysis results provide only an initial indication of the existence of clusters. Since it is a purely exploratory method, it does not provide evidence for their actual existence. It can also be that the algorithm does not identify the correct clusters (Génolini et al. 2013: 11; Schendera 2010: 145). Moreover, it should be noted that other algorithms or an alternative number of clusters *k* may lead to different results. Therefore, caution must be exercised when interpreting the results. Accordingly, running a k-means algorithm can only be a first step in understanding how government responses differed during the COVID-19 pandemic (Teuling et al. 2021: 25).

3.2 Oxford COVID-19 Government Response Tracker

Key data for analysing government responses to the COVID-19 pandemic can be found in the Oxford COVID-19 Government Response Tracker (OxCGRT) database (Hale et al. 2022d), launched by Oxford University researchers in March 2020. For the period from January 2020 to December 2022, scholars gathered information on government responses in 187 countries using publicly available sources such as government press releases or newspaper articles (Hale et al. 2022c: 9). Their goal was to “provide[] a systematic cross-national, cross-temporal measure to understand how government responses have evolved over the full period of the disease’s spread” (ibid.: 4). To ensure comparability across countries and over time, Hale et al. developed a codebook of ordinal, numeric, and binary indicators (2022a). In this thesis, 16 of the ordinal indicators and 12 corresponding flag variables are used, broadly categorised into three groups (see Appendix B):

a) *Containment and closure measures*: closure of schools, cancellation of public events, restrictions on gatherings, restrictions of public transportation, stay-at-home requirements, restrictions on internal movement, and restrictions on international travel;
b) *Economic responses*: income support, debt or contract relief for households, and workplace closings;
c) *Health system responses*: public information campaigns, offer of PCR testing and

vaccination, contact tracing, facial coverings, and protection of the elderly.

Following this categorisation, three indices (Containment and Closure Index (CCI), Economic Response Index (ERI), and Health System Index (HSI)) are calculated using simple averages of the individual component indicators. They provide information about the political stringency of any government on any given day and range from 0 to 100. The higher the score, the more stringent the measures.[10] Moreover, the OxCGRT dataset contains reported coronavirus infections and registered deaths.[11] These data are critical for analysing government responses, as countries are likely to have taken different measures to contain the coronavirus during different phases of the pandemic (Felbermayr et al. 2020: 4).

Given that the OxCGRT dataset forms an integral part of the following analysis, some comments on the limitations of the data must be made. First, although using a codebook with predefined variables and given categories allows for reliability and comparability of the data collected, it prevents the governments' responses from being captured in detail. Nuances in the design of the measures are not recorded or are captured via additional string variables that are not included in this analysis.[12] Second, the dataset contains almost exclusively federal-level data, neglecting differences between subnational regions. In cases where a government implemented measures that differed across regions, the most stringent measure is coded. A flag variable then indicates whether a policy is targeted (Hale et al. 2021: 534; see Appendix B). A third major shortcoming of the data is the lack of information on policy enforcement (ibid.: 535). For example, facial covering might be mandatory. In reality, however, people might not comply because they do not have to fear prosecution. Thus, analysing the effectiveness of government responses is outside the scope of this thesis. Fourth, it is probable that the data are noisy (Kahneman et al. 2021) and, in some respects, are neither comparable nor reliable, given that more than 1,200 data collectors were involved in the data collection (Hale et al. 2022c: 24–38). Hale et al. attempt to address this issue with numerous training and testing sessions for new coders, weekly meetings, and a review process (2021: 535).

Lastly, the numbers of reported COVID-19 cases and deaths should also be interpreted with caution, as they may differ significantly from actual numbers due to differences in "local testing strateg[ies], laboratory capacit[ies] and the effectiveness of surveillance systems" (ECDC 2020). However, this issue can be partially disregarded because governments base their decisions on these figures.[13]

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[10] For more information on the variables and how the indices are calculated, see Appendix B.

[11] The variable of COVID-19 infections strongly correlates with the number of deaths (0.78). Therefore, COVID-19 cases provide sufficient information about a country's exposure to the virus, and the number of deaths is not considered further in the subsequent analysis.

[12] Hale et al. illustrate this problem with an example from 2020 concerning France and the United Kingdom. The stay-at-home requirements were roughly comparable and were therefore coded in the same way. However, this did not take into account that the French government had introduced an additional regulation according to which "French residents had to submit a form to authorities to leave their house" (Hale et al. 2021: 534).

[13] It is possible, though, that not all countries report their actual infection rates to the international community. As a

3.3 Data preparation

More than three years have passed since the first COVID-19 infection occurred (WHO 2022b). During this long period, the pandemic has steadily lost its significance and explosiveness. Since this thesis examines only the initial acute phase of the pandemic, a suitable cut-off point is sought. Countries are expected to have responded significantly differently when there was the prospect of an effective vaccine that would mitigate the most severe COVID-19 cases. Therefore, the end of the period is set when the first country in the world started vaccinating its population, and 0.01% of people had received their first COVID-19 vaccine. To identify this date, the COVID-19 dataset from Our World in Data (Mathieu et al. 2022) is consulted, which provides information on "the number of people [who] received at least one vaccine dose per 100 people in the total population" (Mathieu et al. 2021: 952). It is found that the United States reached the target on December 13, 2020.

In a further step of data preparation, only the first day of each month is kept to reduce the dataset to a manageable amount of data. Furthermore, all rows with missing values are deleted. As a result, the remaining period for the following analysis extends from March 1 to December 1, 2020, with data for ten time points for each country.

The data are further processed for cluster analysis. In a first step, six dimensions are calculated using the variables in the OxCGRT dataset. For the first three dimensions, the indices (CCI, ERI, and HSI) and the number of COVID-19 infections are converted into percent changes from the previous data point to overcome problems of stationary data. Each index is then divided by the number of confirmed cases to capture different phases of the pandemic. The three resulting dimensions are named as follows:

(1) *conclos_cases*, i.e., ratio of CCI to COVID-19 cases
(2) *econ_cases*, i.e., ratio of ERI to COVID-19 cases
(3) *health_cases*, i.e., ratio of HSI to COVID-19 cases

Another three dimensions are intended to measure a government's adaptability. Three new variables are calculated, yielding a value of +1 if measures (CCI, ERI, and HSI) were set up from the previous month, a value of -1 if measures were dismantled of the prior data point, and a value of 0 if no change was recorded. A fourth variable captures the increase (+1), decrease (-1), or continuity (0) in the number of new cases. The value of change in COVID-19 cases is then subtracted from the value of change in CCI, ERI, and HSI to create three dimensions. The meaning of the resulting values can be found in Figure 6$_A$.[14] For example, a score of +2 means that a government has taken much stricter action than would be expected in relation to COVID-19 cases. In other words, the government implemented stringent measures even though the number of cases had decreased compared to the previous month. A value of 0

result, the dataset may contain embellished data.

[14] Figures or Tables marked with a subscript letter A are in Appendix A.

indicates that the government is perfectly adjusting to the increase or decrease in COVID-19 cases by dismantling or setting up its responses accordingly. The three resulting dimensions are named as follows:

(4) *conclos_updown_cases*, i.e., relationship between a change in CCI and COVID-19 cases
(5) *econ_updown_cases*, i.e., relationship between a change in ERI and COVID-19 cases
(6) *health_updown_cases*, i.e., relationship between a change in HSI and COVID-19 cases

In a second step, extreme outliers are removed from the dataset. This step is performed because the k-means algorithm, which is based on the mean, is sensitive to outliers. They shift the position of the cluster centre in their direction (Teuling et al. 2021: 8; Morissette/Chartier 2013: 16; Schendera 2010: 144). Upper and lower bounds are set at 0.1% of the data points per dimension.[15] Since trends over time are of primary interest, countries are identified for the outliers found and removed as a whole. After excluding Estonia, Hungary, Iran, Japan, the Marshall Islands, Panama, the Philippines, Poland, and Turkey from the dataset, 175 countries and no missing values remain for the subsequent analysis.

In a third step, correlations between the six dimensions are calculated. It is found that the fourth, fifth, and sixth dimensions are highly correlated (about 0.64; Figure 7[A]). Since variables used in a cluster analysis should not be highly correlated (Stahlberg et al. 2022: 94), the cluster analysis comprising all six dimensions should be interpreted with caution. Finally, the data are z-score standardised, another requirement for k-means cluster analysis (Génolini et al. 2013: 106; Schendera 2010: 144), such that the mean is zero and the standard deviation is one across all dimensions.

3.4 Longitudinal cluster analysis in R

As explained in Section 3.1, a k-means cluster analysis is performed using R. The *kml3d* package contains a suitable "K-Means [Algorithm] for Joint Longitudinal Data" (Génolini et al. 2022). It can process multiple longitudinal variables, so-called "joint-trajectories" (Génolini et al. 2015: 2).[16] To obtain results that can be used to answer the above research question, the cluster analysis is performed four times for all 175 countries and ten time points. The analyses differ in their input variables: First, all dimensions are entered (*all_all*). In three further analyses, dimensions (1) and (4), (2) and (5), and (3) and (6) are inputted, respectively, resulting in outcomes named *all_conclos*, *all_econ*, and *all_health*. It should be noted that "each variable has equal influence in the formation of clusters" (Attewell/Monaghan 2015: 198).

The package of Génolini et al. requires that five steps be performed to determine the clusters:

(1) The first step is to transform the dataset into an object of class *ClusterLongData3d,* which stores information about the cases, the input variables, and the longitudinal data (Génolini

[15] A higher threshold was not applicable. Otherwise, too many countries would have been excluded.

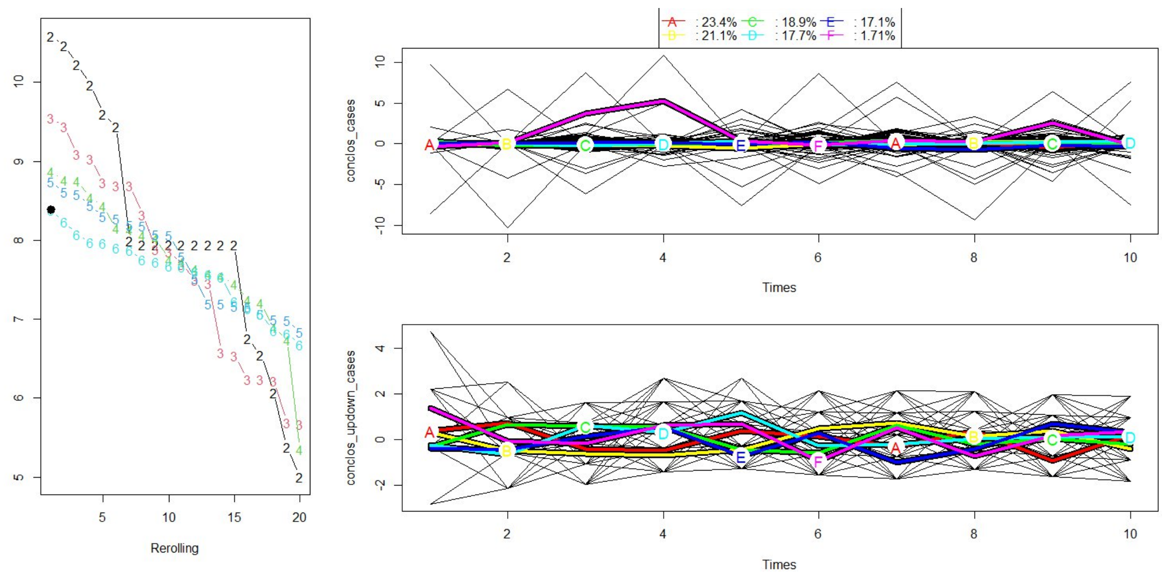
[16] A trajectory of a case i is defined as "a sequence of n_i observations by $y_i = \left\{y_{i,1}, y_{i,2}, \ldots, y_{i,n_i}\right\}$, where the observation $y_{i,j}$ is taken at time $t_{i,j} \epsilon \mathbb{R}$" (Teuling et al. 2021: 2).

et al. 2015: 14f.).

(2) Then, the kml3d() function is executed to find the optimal partition (Génolini et al. 2015: 15). Contrary to the claim in Section 3.1 that partitioning approaches such as the k-means algorithm require a predefined number of clusters (Attewell/Monaghan 2015: 203), the kml3d() function varies the number of potential clusters by default between two and six. Furthermore, it runs the k-means algorithm 20 times from the beginning (Génolini et al. 2015: 15f.). This avoids finding only a local minimum solution (Morissette/Chartier 2013: 18). The algorithm also computes the value of several quality criteria that indicate whether the partition found is 'good', i.e., whether the clusters are strongly homogeneous within the cluster and strongly heterogeneous between the clusters (Backhaus et al. 2018: 490).[17]

(3) Subsequently, the results are visualised with the choice() function. Two types of charts are displayed side by side. For example, Figure 1 depicts the cluster analysis result of *all_conclos* with the two dimensions *conclos_cases* and *conclos_updown_cases*. On the left side, all partitions found by the algorithm are displayed. An integer indicates the number of clusters (here: 2 to 6) in the respective partition. The x-axis shows the number of redrawings. On the y-axis, the value of a quality criterion is plotted. By pressing certain keys, another criterion can be selected and displayed (Génolini et al. 2015: 17f.). On the right side, the mean trajectories of the partition selected in the left graph (marked by the black dot in Figure 1) are faceted by variable (ibid.). The graphs "plot[] the longitudinal data and highlight[] the cluster structure of the selected partition using colors" (ibid.: 17). A legend indicates how many cases (here: countries) are assigned to a cluster.

Figure 1 – kml3d() results for the *conclos_cases* and *conclos_updown_cases* dimensions



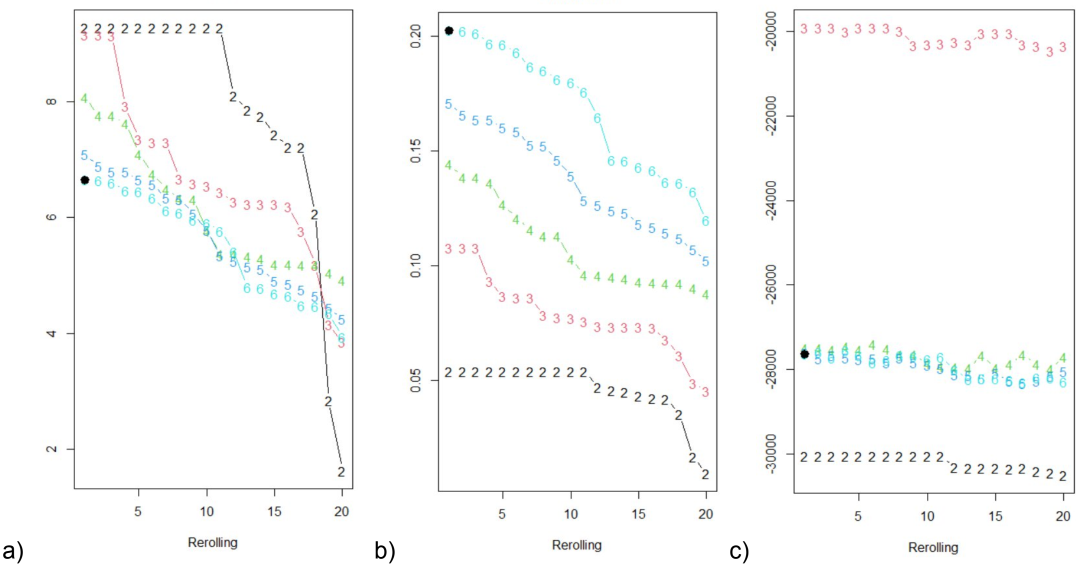
(Own figure based on calculations with data from the OxCGRT database (see 3.2). For information on the dimensions, see Section 3.3. A k-means cluster analysis for joint longitudinal data (see 3.1) is performed in R with

[17] Among the quality criteria computed by the kml3d algorithm are the Calinski and Harabasz criterion, the Calinski and Harabasz criterion, Kryszezuk variant, the Calinski and Harabasz criterion, Genolini variant, the Ray and Turi criterion, and the Davies and Bouldin criterion (Génolini et al. 2015: 9f.). They are all well-known in the scientific community for their dependability (ibid.: 4).

the kml3d() function. The chart on the left shows the value of a quality criterion for all partitions found. The Calinski and Harabasz criterion appears first by default. The partitions are represented by their respective numbers of clusters. Here, the partition with six clusters (A–F) is selected, marked by the black dot. For selection criteria, see below. On the right side, the mean trajectories of the selected partition are displayed. The x-axis shows the ten time points of the data, i.e., the first day of each month between March (= 1) and December 2020 (= 10).)

(4) When deciding on the appropriate number of clusters, "a number of different values for k (usually over a range)" (Attewell/Monaghan 2015: 204) should be tried until the best solution is found. Several factors must be considered when selecting the most appropriate partition. The quality criteria, which indicate the optimal number of clusters, are of the greatest importance (McNulty 2020). To simplify the capture of results, the kml3d package "compute[s] the criteria that should be maximized, and compute[s] the opposite of the criteria that should be minimized" (Génolini et al. 2015: 11). As a result, regardless of the active criterion, the cluster number that achieves the maximum value of the criterion should be selected (ibid.). However, different quality criteria may indicate different appropriate cluster numbers, as exemplified by Figure 2.[18] Caution is also advised when the graph shows a "big drop in quality" (McNulty 2020) from left to right (see, e.g., partition 2 in Figure 2a). Additionally, the relative and absolute size of each cluster should be considered. It is not particularly useful if two clusters are identified, one of which consists of only one or two cases out of 175 (Bahrenberg et al. 2008: 272; McNulty 2020). Moreover, the trajectories should be examined. If patterns can be seen in the right-handed charts, the number of clusters chosen may be optimal (ibid.).

Figure 2 – kml3d() results of three selected quality criteria for *all_all* cluster analysis



(Own figure based on calculations with the kml3d() function in R. A k-means cluster analysis for joint longitudinal data (see 3.1) is performed with six dimensions, which is calculated using data from the OxCGRT database (see 3.2). The charts show the value of three quality criteria for all partitions found: (a) Calinski and Harabasz criterion, (b) Calinski and Harabasz criterion, Kryszczuk variant, and (c) Akaike information criterion with correction for finite sample size. Partitions are represented by their respective cluster numbers.)

(5) After the decision about the partition and thus the number of clusters has been made, the

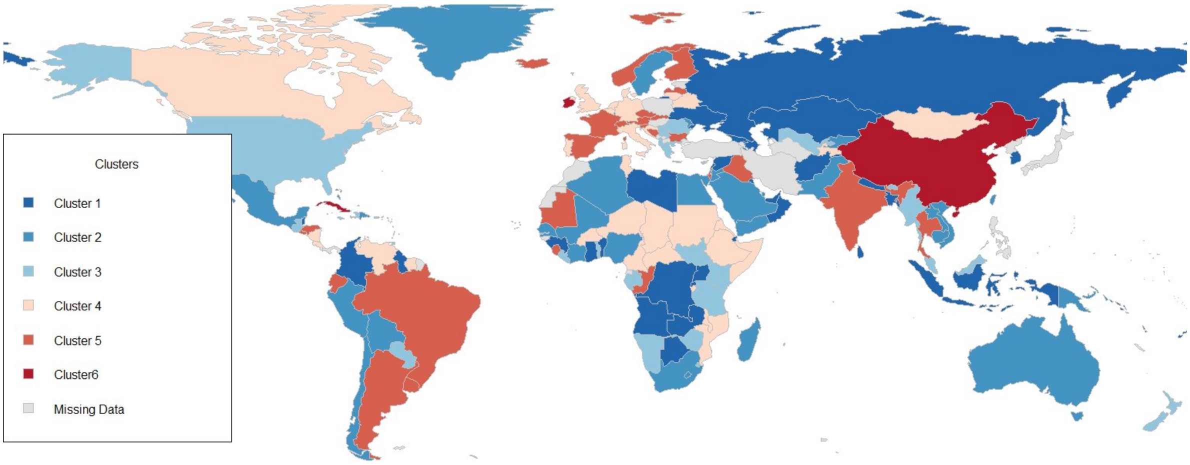
[18] As mentioned in Section 3.1, no quality criterion that perfectly determines the optimal number of clusters can be identified. Therefore, it is assessed whether several criteria point to the same number of clusters, as this is a good indication of their reliability (Génolini et al. 2015: 4).

partition is selected by pressing the space bar (Génolini et al. 2015: 17). R then saves two CSV files. One of them documents the assignment of each case (country) to a cluster.[19] The second file contains information about the size of the selected clusters and the corresponding value for each quality criterion (Table 1A).

3.5 Cluster analysis results

The results of the four cluster analyses (*all_all*, *all_conclos*, *all_econ*, and *all_health*) are examined below. The cluster analysis using all six dimensions identifies six clusters, but three comprise only a small number of countries (1, 2, and 9, respectively) (Table 1A, Column 2). The outliers deviate strongly in all dimensions (Figure 8A) and include Australia, China, Germany, Kenya, Libya, Uganda, and Vietnam (Figure 9A). To gain a deeper insight into the trends of the dimensions over time, the mean trajectories are plotted again, but without the outlier clusters (Figure 10A). Across all dimensions, the means of countries in cluster 3 swing sharply, while those in clusters 1 and 2 deviate from 0 to a lesser extent, with a few exceptions. It should be noted, however, that high correlations between the fourth, fifth, and sixth dimensions reduce the informational value of the *all_all* cluster analysis results (see 3.3).

Figure 3 – World map of cluster analysis results including only CCI dimensions



(Own figure based on the results of a k-means cluster analysis for joint longitudinal data (see 3.1) with the dimensions conclos_cases and conclos_updown_cases (see 3.3), which are calculated using data from the OxCGRT database (see 3.2). The results are plotted on the world map using the rworldmap package in R.)

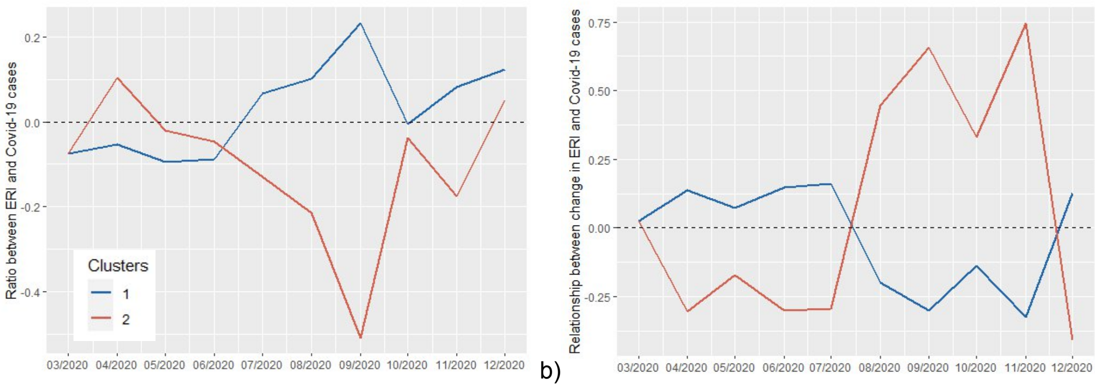
The selected partition of the cluster analysis with the dimensions *conclos_cases* and *conclos_updown_cases* comprises six clusters (Table 1A, Column 3). Only three countries are assigned to the sixth cluster: China, Cuba, and the Republic of Ireland (Figure 3). These countries diverge upward in the ratio of CCI to COVID-19 cases between April and July 2020 (Figure 1). All other countries are roughly evenly distributed across the remaining clusters (Table 1A, Column 3). No clear patterns emerge for these clusters, as can be seen when the outlier cluster is removed from the charts of the mean trajectories (Figure 11A). The average ratio of CCI to COVID-19 cases ranges from -0.25 to 0.25 in all five remaining clusters until June 2020, after which the means move more up and down. For example, countries in cluster 5

[19] Using the rworldmap package (South 2011), these data are displayed on world maps (Figures 3, 9A, 13A, 15A).

have a strongly negative ratio from September to December, while the mean value of cluster 3 peaks in September (Figure 11a[A]). Interestingly, only countries in cluster 1 implemented more stringent measures in both March and April 2020, while countries in clusters 4 and 5 responded more softly than might be expected with respect to new COVID-19 cases (Figure 11b[A]). This pattern is assessed in more detail in Section 4.4.

Four clusters are identified in the *all_econ* cluster analysis (Table 1[A], Column 4). While 66% of the countries are represented in the first cluster, only Germany, Honduras, Kenya, and China are found in the third and fourth clusters (Figure 13[A]). At the beginning of the period studied, the ratio of ERI to COVID-19 cases reaches a peak in the latter clusters, and the third cluster also deviates negatively in December 2020 (Figure 12[A]). Again, the mean trajectories are plotted without the outlier clusters (Figure 4). On average, countries in cluster 1 have a smaller ratio of ERI to COVID-19 cases than countries in cluster 2 until June 2020. Then, this pattern reverses, and countries in cluster 2 experience a sharp decline in the ratio. In September, both groups of countries diverge sharply from 0, implying that their ERI changes more than the number of cases compared with the previous month (Figure 4a). A similar dichotomy is observed in the relationship between a change in ERI and COVID-19 cases. Countries in cluster 1 show positive values until July 2020, implementing more stringent measures than would be expected in relation to COVID-19 cases. Thereafter, the mean of cluster 1 is negative, indicating relatively soft measures. The opposite is true for countries in cluster 2 (Figure 4b).

Figure 4 – Mean trajectories without outlier clusters of the *all_econ* cluster analysis



a)

(Own figure based on the results of a k-means cluster analysis for joint longitudinal data (see 3.1 and 3.4) with the dimensions econ_cases and econ_updown_cases (see 3.3), which are calculated using data from the OxCGRT database (see 3.2). The selected partition includes four clusters, but two contain only a small number of cases. To examine the differences between the larger clusters in more detail, their means are plotted again without the outlier clusters. Graph a displays changes in the econ_cases dimension, while graph b shows trends in the econ_updown_cases dimension. The data are z-score standardised.)

The final partition of the *all_health* cluster analysis comprises five clusters (Table 1[A], Column 5). More than 90% of countries are almost evenly distributed among the first three clusters, while the fourth and fifth clusters include only India, Lebanon, and Yemen (Figure 15[A]). As in the *all_econ* cluster analysis, these countries show peaks in the *health_cases* dimension (Figure 14[A]). The chart displaying the average ratio of HSI to COVID-19 cases (excluding the outlier clusters) (Figure 16a[A]) shows several substantial deviations (positive and negative) from a value of 0 in all clusters. The highest peaks occur in March, May, June, and September 2020, indicating that in these months, the stringency of government responses, as measured by the HSI, changes more from the previous month than the number of COVID-19 cases. Looking more closely at the relationship between changes in HSI and COVID-19 cases (Figure 16b[A]), an opposite trend can be observed between May and September between countries in cluster 1 and those in cluster 3. Governments assigned to the first cluster implemented, on average, less stringent policies through July than would have been expected with respect to COVID-19 cases. Thereafter, they acted more stringently. The opposite is true for governments in cluster 3, while governments in cluster 2 have consistently adopted more stringent actions over this period.

4. Characterisation of the clusters

Having identified several clusters, it is worth asking what distinctive features account for their composition. Following NIE, this thesis assumes that institutional differences can explain some of the variations in government responses. Accordingly, this section is devoted to characterising the clusters. Section 4.1 describes the institutional variables and their hypothesised effects on government stringency. A brief description of data preparation (4.2) and the statistical method of analysis of variance (ANOVA) (4.3) precede the summary of the final results (4.4).

4.1 Selection of institutional variables

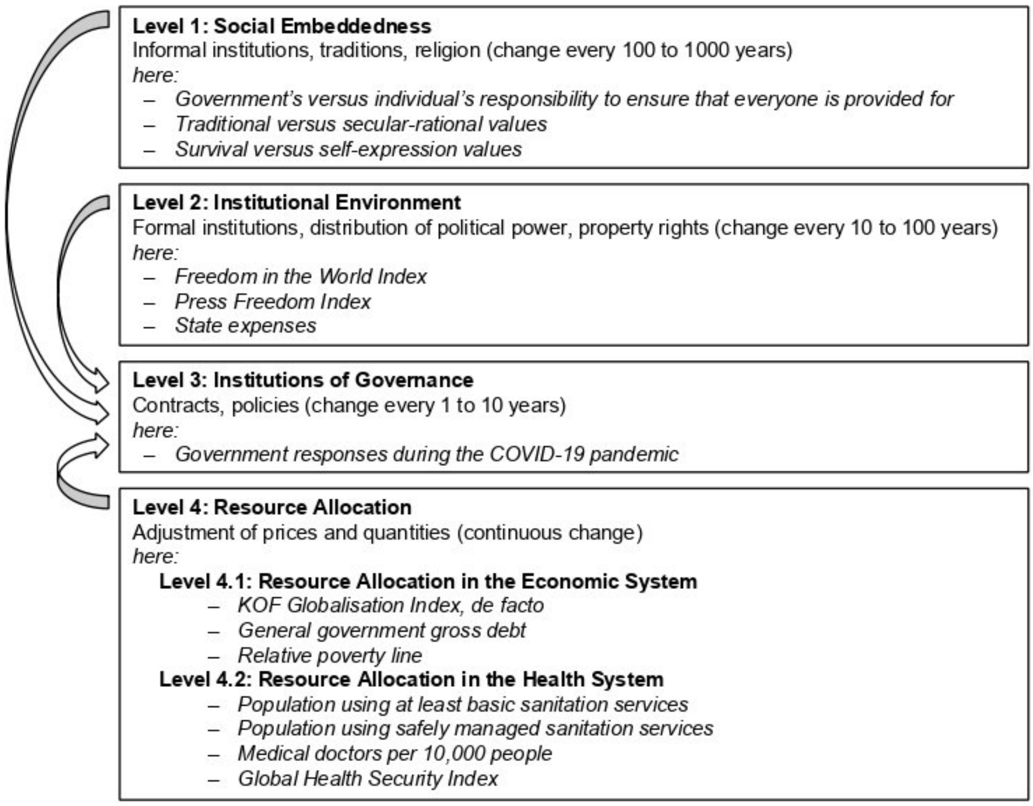
The results of the cluster analyses are merged with datasets containing 14 metric institutional variables and two metric control variables. As explained in Section 2, Williamson's typology plays a critical role in selecting the variables. Williamson identified four levels of institutions, i.e., social embeddedness, institutional environment, governance, and resource allocation, which differ in the frequency of their change (Williamson 2000: 596–600). Figure 5 summarises the classification of each selected variable into one of the four levels of institutions.

4.1.1 Level 1: Social Embeddedness

According to Williamson, informal institutions, traditions, and religion (indirectly) affect institutions of governance (Williamson 2000: 596f.). To assess whether this also applies to government responses as third-level institutions, three variables are included in the analysis that provide information about the values of a society through the aggregation of representative survey data.[20]

[20] Such data are an imperfect measure of cultural orientations as they capture only some informal institutions (Bentkowska 2021: 732). Responses may be biased due to social desirability, and general statements about the desired role of government may be influenced by attitudes towards the government currently in power. In addition, the meaning of scores on an ordinal scale varies between individuals. Finally, some words may have different meanings in different societies, which affects the international comparability of responses. Nevertheless, the variables selected provide some indication of the culture of a society.

Figure 5 – Institutional variables classified according to Williamson's typology



(Own figure based on Williamson 2000: 596–600)

An example of such a representative survey is the World Values Survey (WVS), which collected data on the values and beliefs of people in 59 countries in its seventh wave. In face-to-face interviews, respondents were asked numerous questions about norms, perceptions, political interest, and activism (Haerpfer et al. 2020b; 2022f; 2022d: 1). One of the questions on economic values concerned **government versus individual responsibility**. Respondents were asked to indicate their (dis)agreement with two contrasting statements: "The government should take more responsibility to ensure that everyone is provided for" (ibid.: 40) and "People should take more responsibility to provide for themselves" (ibid.). The response options ranged from 1 to 10 on an ordinal scale. Respondents who believed (more) in the responsibility of the state chose a low value, while respondents who felt (primarily) that the individual was responsible chose a high value (ibid.). The individual-level data are combined into country-level means. It is assumed in the following that people who emphasise the responsibility of the state are in favour of government action. Therefore, in societies with a low mean on this variable, governments are expected to be stricter and respond more rapidly across all dimensions (i.e., CCI, ERI, and HSI).

Moreover, this thesis takes general cultural orientations into account. After conducting a factor analysis of ten items from the WVS and the European Values Study (Haerpfer et al. 2022b),[21]

[21] The variables are "feeling of happiness", "most people can be trusted", "future changes: greater respect for authority", "political action: signing a petition", "how important is God in your life", "justifiable: homosexuality", "justifiable: abortion", "how proud of nationality", "Post-Materialist index 4-items", and "Autonomy Index" (Haerpfer et al. 2020a).

researchers Inglehart and Welzel found “two major dimensions of cross cultural [sic] variation in the world: **traditional values versus secular-rational values** and **survival values versus self-expression values**” (Haerpfer et al. 2022c, emphasis in the original). In societies where traditional values predominate, people attach great importance to religion, authority, children’s obedience, and national identity. Secular-rational values embody the opposite and are typically associated with acceptance of divorce, abortion, euthanasia, and suicide. People guided by survival values seek economic and physical security and a strong government. They tend to show low levels of tolerance, trust, and well-being. In contrast, people oriented towards self-expression values support gender equality and environmental protection. They are individualistic and want to participate in decision-making processes (Haerpfer et al. 2022b; Inglehart 2006: 118–125). The assumption here is that governments ruling a traditionally oriented society with a strong emphasis on survival values have greater leeway in implementing regulations. This is because people in these societies place less value on personal freedom. State regulations restricting individual freedom (measured in CCI and HSI) are, therefore, more controversial in societies where self-expression and secular-rational values prevail. This assumption is consistent with other research findings on individualistic versus collectivistic societies (Chen et al. 2021: 2, 5).

4.1.2 Level 2: Institutional Environment

Williamson further assumes that formal institutions, the distribution of political power, and property rights impact third-level institutions (Williamson 2000: 598) and, thus, government responses. The three variables included in this thesis provide information on a country’s political system (Freedom in the World Index), its media system (Press Freedom Index) and its overall state power (measured by state expenses).

With its **Freedom in the World Index**, the non-governmental organisation (NGO) Freedom House aims to measure a people’s political rights and civil liberties. Various experts gather information on de jure and de facto freedom by studying relevant sources and conducting on-site research. The categories assessed include the electoral process, political pluralism and participation, functioning of the government, the rule of law, personal autonomy, and individual rights. A score between 0 and 100 is obtained, with a high value representing a free country (Freedom House 2020: 1ff.). Another classification that focuses on the media, the **Press Freedom Index**, is compiled by the NGO Reporters Without Borders (RSF). Qualitative evaluations and quantitative data are combined to form an index that outputs values between 0 and 100, with a high value indicating free press. Variables used to calculate the index include independence of the media, pluralism, transparency, media environment, self-censorship, and violence against journalists (RSF 2021b).[22]

[22] Indices such as those mentioned above aim to compare numerous different political systems using standardised assessments. It is questionable whether they succeed in capturing the complexity inherent in any political system (Marschall 2014: 69, 77). Moreover, democracy indices such as the Freedom House Index measure all countries

No hypothesis can be formed about the effects of a country's political system and freedom of the press on the stringency and timing of government responses, as researchers have found two ambiguous results. On the one hand, democratically elected governments may implement measures more rapidly as they want to be re-elected. If their voters, who can easily follow their performance through the free media, demand decisive action, politicians will respond quickly to the pandemic outbreak. On the other hand, democratic decision-making involves debates among numerous individuals and interest groups, and every new law must be examined for its compatibility with the constitution. This process often takes a long time. Moreover, politicians are likely to delay the implementation of government responses if they are confronted with a critical assessment of their proposed policies in the free media (Alon et al. 2020: 157f.; Besley/Dray 2023; Chen et al. 2021: 2, 5; Legiędź 2021: 594; Toshkov et al. 2022: 1016).

In contrast to the ambivalent effects of a country's degree of freedom, this thesis assumes a clear relationship between state power and government responses: a powerful state is likely to adopt more stringent measures in all dimensions of action more quickly because the government is aware of its enforcement power. As an indicator of a state's power and its ability to effectively enforce property rights, data on **government expenses**, measured as a percentage of gross domestic product (GDP), are included in the analysis. The World Bank records all "cash payments for operating activities of the government in providing goods and services" (The World Bank 2022a). As the data collection is mainly based on questionnaires to governments, some figures might be inaccurate, incomplete, and difficult to compare (ibid.).

4.1.3 Level 4.1: Resource Allocation in the Economic System

When policymakers decided on restrictions to slow the spread of the virus, they also had to consider the country's economic resource allocation. First of all, a country's degree of globalisation likely limited the government's room for manoeuvre. A high frequency of trade and international contacts accelerates the transmission of the virus. Accordingly, this thesis assumes that countries with a high level of global connectivity had to respond faster and more stringently, particularly by implementing containment and closure measures. The **KOF Globalisation Index** is a suitable index that quantifies a country's degree of globalisation. It is compiled by researchers at the Swiss Federal Institute of Technology and provides values on a scale of 0 to 100, with a high score indicating a high degree of globalisation (Gygli et al. 2019: 544, 558). It aggregates economic, social, and political data on "actual [i.e., de facto] international flows and activities" (ibid.: 544), such as trade volume, trade partner diversity, international reserves, international tourism, and migration (Gygli et al. 2022a).[23]

"against the standard format of a Western democracy, which in historical concretion is based on prosperity, market economy, and individualistic culture" (Hartmann 2015: 147, translation my own).

[23] Besides the de facto index, Gygli et al. also provide a de jure index that "measures policies and conditions that, *in principle*, enable, facilitate and foster flows and activities" (2019: 544, emphasis added), such as trade regulations, freedom of visit, and international treaties (Gygli et al. 2022a). The de jure KOF Globalisation Index thus tracks formal institutions (level 2) or institutions of governance (level 3) that promote or inhibit global trade and

Furthermore, fiscal constraints are likely to confine governments' ability to act. This thesis assumes an inverse relationship between a country's ERI and **general government gross debt**, measured as a percentage of GDP. The International Monetary Fund (IMF) defines government debt as "all liabilities that require payment or payments of interest and/or principal by the debtor to the creditor at a date or dates in the future" (2022). Governments facing serious debt problems are likely to have little or no means to provide income support to people who cannot work or have lost their jobs and to compensate for freezing financial obligations and closing workplaces.

Finally, societies with greater social inequality are expected to have had higher government spending (i.e., a higher ERI) during the COVID-19 pandemic because a relatively large portion of the population is poor and, thus, particularly vulnerable. Low-income people often work in low-skill, non-essential sectors that suffer more from recessions and were shut down during the pandemic.[24] Moreover, poor people usually have fewer possibilities to work remotely and little savings to compensate for income losses (Blundell et al. 2022: 609, 620; Darvas 2021: 1, 12). Anticipating a further rise in inequality due to the pandemic, governments presumably sought to prevent this development through fiscal measures.[25] To assess whether this assumption holds, data on the **relative poverty line** are included in the analysis. Hasell and Arriagada provide figures on the percentage of the population "living in households with an income or expenditure per person below 50% of the median" (2023).[26]

4.1.4 Level 4.2: Resource Allocation in the Health System

Finally, the "capacity [of a country] to deal with health emergencies" (Toshkov et al. 2022: 1014) played a critical role in governments' decisions. In general, the less prepared a country is to handle large numbers of infected people, and the poorer the overall sanitation, the more vulnerable the country is to a severe pandemic outbreak. As decision-makers wanted to avoid a collapse of the healthcare sector at all costs, they often based their decisions on the robustness of their health systems (Tooze 2021: 56). Countries that score poorly on the following indicators are, therefore, likely to act rapidly and adopt stricter regulations to prevent the spread of the virus by restricting interpersonal contact and adopting health measures (i.e., higher scores on CCI and HSI).

The WHO collects information on access to sanitation through censuses, household surveys,

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transnational interactions. Therefore, it also serves as a valid institutional variable. However, since the worldwide spread of a pandemic hinges on the *actual* existence of cross-border contacts, the de facto index was chosen here.

[24] In the United Kingdom, for example, "less than 50% of those in the bottom decile of the earnings distribution worked in sectors that remained open, [while] over 90% in the top decile did so" (Blundell et al. 2022: 620).

[25] Indeed, researchers have observed an increase in inequality and poverty: "The income of the poorest 20 percent experienced a sharper decline in 2021 compared to a higher income group. This decline in income has translated into around 100 million more people living in extreme poverty" (Ghecham 2022: 3). Almeida et al. found that policies implemented in the EU in 2020 likely reduced the increase in inequality, as measured by the Gini index, by 4.7 percentage points (2020: 13).

[26] The data were collected through household surveys by the World Bank and "measure people's income in high-income countries, and people's consumption expenditure in poorer countries" (Hasell/Arriagada 2022).

and measurements by national authorities. Lack of access increases the risk of infection and death (WHO 2021a). One variable measures the **percentage of the total population using at least basic sanitation facilities**, i.e., “improved sanitation facilities that are not shared with other households” (ibid.). Another variable records the proportion of the population that uses **safely managed sanitation services**, i.e., “improved sanitation facilit[ies] that [are] not shared with other households and where excreta are safely disposed of” (WHO 2021b).

The WHO database also contains national-level information on the number of **medical doctors**, i.e., generalist and specialist physicians, **per 10,000 people**.[27] It is based on figures provided by governments and collected through censuses, surveys, and regional administrative sources (WHO 2022a). Experts estimate that 25 health workers per 10,000 inhabitants can be considered a benchmark for adequate primary healthcare (WHO 2006: 11). Consequently, if the number in a country is below 25, “the public’s health suffers” (ibid.: 10).

Lastly, the **Global Health Security Index** assesses “the existing capacities of countries to prevent, detect, and respond to outbreaks [of infectious diseases]” (NTI et al. 2021b: 3). Researchers of the non-profit organisation Nuclear Threat Initiative (NTI), the Johns Hopkins Center for Health Security, and the think tank Economic Impact rely on publicly available sources to calculate the scores (ibid.: 6, 14). The categories assessed include the prevention of the emergence or release of pathogens, early detection and reporting of epidemics of potential international concern, rapid response to an epidemic and containment of its spread, and the overall vulnerability of the country to biological threats. The scale ranges from 0 to 100, with a high value indicating “favorable health security conditions” (ibid.: 6f.).

4.1.5 Control variables

Finally, two control variables are included. The World Bank provides information on a country’s **gross domestic product** (GDP) **per capita**, measured in current U.S. dollars. GDP is defined as “the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products” (The World Bank 2022b). The variable indicates the performance and size of an economy (Callen 2017: 15).[28] It is assumed that rich countries tend to have sufficient capacity to implement costly measures of any kind (Tooze 2021: 150; Toshkov et al. 2022: 1013).

The analysis also controls for the **unemployment rate**, measured as a percentage of a country’s total labour force. Unemployment is defined as “without work but available for and seeking employment” (The World Bank 2022c). The World Bank compiles data from nationally reported sources, such as those based on surveys. Missing data are estimated by the International Labour Organization. A high value of this variable over several years indicates

[27] It should be noted that there are often significant differences between the density of health workers in rural and urban areas (WHO 2006: 8).

[28] Data may be inaccurate in countries where the national statistical agency does not adhere to international standards and the informal sector is large (Callen 2017: 14; The World Bank 2022b).

inefficiencies in the labour market, uncertainties, and lower levels of innovation and competitiveness (The World Bank 2022c). Following Ping Ang and Dong's findings, it is hypothesised that higher unemployment leads to lower government stringency. The reason is that governments face a trade-off between keeping the number of unemployed low and preventing new COVID-19 cases. In other words, when policymakers adopt more stringent responses, on the one hand, they prevent the spread of the virus, but at the same time, they increase the number of unemployed (Ping Ang/Dong 2022: 1280f., 1288–1292).[29]

4.2 Data preparation

Before discussing the results of the analysis, three remarks about the selection and preparation of all variables are required. First, most of the data are from 2019 or earlier,[30] as this thesis is intended to draw inferences from institutional variables to government responses. Otherwise, there is a possibility that the aftermath of the COVID-19 pandemic has significantly altered the institutions (Czetwertyński/Sukiennik 2021: 572).

Secondly, in some cases, ISO-3 country codes and country names need to be recoded since they appear in the OxCGRT dataset with different names. Otherwise, the information for these countries would be lost when the datasets are merged. Since some datasets do not contain any ISO-3 country codes, the cepiigeodist package with ISO-3 country codes and full English names of each country is used to merge the data (Vargas 2020: 3).

Thirdly, the institutional variables are combined into four separate datasets, each representing one institutional level (see 4.1.1 to 4.1.4). The control variables (see 4.1.5) and the results of the cluster analyses (see 3.5) are added to all four datasets. Finally, all rows with missing data are deleted to simplify further analysis. Only 50 countries remain in the social embeddedness dataset. At each of the other levels, there are over 100 complete cases (Table 2[A]).

4.3 Analysis of Variance

To assess whether the selected institutions can indeed explain some of the variation in government responses, an analysis of variance (ANOVA) is run using the aov() function of the stats package in R. This method computes the variance between groups over the variance within groups and provides an F-statistic value (Kim 2014: 75). The larger the F-statistic value, the larger the differences between the means of the groups, and the more likely the null hypothesis can be rejected (ibid.), which states that "differences in means do not exist" (Kim 2017: 22). Moreover, eta squared is computed, which provides information on effect sizes, i.e., "the proportion of the total variance in a dependent variable that is associated with the membership of different groups defined by an independent variable" (Richardson 2011: 135).[31]

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[29] Since more stringent government responses result in higher unemployment (Ping Ang/Dong 2022: 1288–1292), this constantly changing variable provides sufficient information only for the first month studied.

[30] Table 2[A] provides an overview of the year(s) from which the selected variables are drawn.

[31] Eta squared is calculated as follows: $\eta^2 = \frac{\text{sum of squares for the effect of the independent variable}}{\text{total sum of squares}}$ (Richardson 2011: 136).

The subsequent analysis focuses only on those clusters that show contrasting developments in their mean scores on one of the six dimensions compared to other clusters (see 3.5).[32] Since the response variable of an ANOVA cannot be nominal, the variables indicating assignment to a cluster are recoded into binary variables.[33]

As discussed in Section 3.5, in the *all_conclos* cluster analysis, countries in cluster 1 responded, on average, with greater stringency relative to COVID-19 cases in both March and April 2020 (Figure 11b[A]). In contrast, countries in cluster 2 (cluster 3) responded more stringently only in March (April), whereas countries in clusters 4 and 5 implemented softer measures in both months. For the subsequent analysis, cluster 1 is assigned a value of 0, and both clusters 4 and 5 are assigned a value of 1. All other clusters are excluded from the analysis.

In the *all_econ* cluster analysis, countries in clusters 1 and 2 responded conversely to each other on average in both dimensions (*econ_cases* and *econ_updown_cases*; Figure 4). On the latter dimension, countries in cluster 1 responded more stringently until July 2020. Thereafter, the relationship is negative. The opposite is true for countries in cluster 2. Accordingly, the two clusters are recoded as 0 for countries in cluster 1 and 1 for countries in cluster 2, whereas the outlier clusters 3 and 4 are excluded from the analysis.

Lastly, in the case of the *all_health* cluster analysis, institutional differences between countries in clusters 1 and 3 are assessed. Between May and September 2020, the mean trajectories of these two clusters diverge in opposite directions on the two dimensions *health_cases* and *health_updown_cases* (Figure 16[A]). While countries in cluster 3 were more stringent until July and less stringent until September (in relation to COVID-19 cases), countries in cluster 1 responded conversely. Again, a binary variable is coded with a value of 0 for countries in cluster 3 and a value of 1 for countries in cluster 1. Clusters 2, 4, and 5 are excluded from the analysis.

Four ANOVAs are run for each of the *all_conclos*, *all_econ*, and *all_health* cluster analysis results (one ANOVA per institutional level), using the institutional variables from Section 4.1 as predictor variables (Tables 3[A] through 5[A]).[34] Selected outcomes are then plotted to provide an overview of the actual differences in means (Figures 17[A] through 19[A]).[35]

[32] The results of the cluster analysis, which includes all six dimensions, are not further analysed due to the high correlations between the fourth, fifth, and sixth dimensions (Section 3.3 and Figure 7[A]).

[33] In principle, using a binary response variable violates several requirements for the ANOVA method (Lunney 1970: 264). However, Lunney found that an ANOVA can be run if p (here, the proportion of countries in the smaller category) is at least 0.2 and the sample size exceeds 20. If p is less than 0.2, the sample size must exceed 40 (ibid.: 267). Lüpsen assumed an unbalanced design in his study and suggested a value of p between 0.3 and 0.7 (Lüpsen 2019: 14, 19). Because outlier clusters comprising only a small number of countries are excluded, and clusters are merged in this thesis, p is greater than 0.3 with one exception: in the ANOVA with results of the *all_health* cluster analysis with explanatory variables of the social embeddedness level, p is about 0.29.

[34] Due to the scope of this thesis, no interaction terms are included.

[35] In this case, R does not control for other institutional variables.

4.4 Cluster characterisation results

The first four ANOVAs with the results of the *all_conclos* cluster analysis as the response variable yield significant results for four institutional variables: the Freedom in the World Index (level 2), the KOF Globalisation Index (level 4.1), government gross debt (level 4.1), and the Global Health Security Index (level 4.2) (Table 3[A]). The p-values below 0.01 and 0.05, respectively, indicate that the group means are significantly different. Moreover, Eta squared points to relatively large effects of the survival versus self-expression values variable (level 1), given the small number of countries assessed. This institutional factor can explain about 10.7% of the variance in the cluster analysis results.[36] All other institutional variables show negligible effects.[37] Overall, much of the variance remains unexplained (Table 3[A]).

To further assess how institutional differences may explain the fact that countries in cluster 1 responded more stringently in March and April 2020, while countries in clusters 4 and 5 responded more softly, boxplots are drawn for the above five explanatory variables (Figure 17[A]). They show that governments were more likely to respond with stricter containment and closure measures early in the pandemic in the following cases:

a) When survival values prevail in society (Figure 17a[A]). This finding is consistent with the assumption in Section 4.1.1. As a reminder, people who are guided by survival values seek economic and physical security and a strong government. They value personal freedom less than people oriented towards self-expression values (Haerpfer et al. 2022b). Therefore, they might be more accepting of stricter measures.
b) When the political system is less free (Figure 17b[A]). Accordingly, the complex policy-making process in democracies seems rather to prevent the decisive enforcement of measures, as assumed in Section 4.1.2.[38]
c) When the country is less globalised (Figure 17c[A]). This outcome contradicts the assumption in Section 4.1.3 that more globalised countries adopted measures more rapidly to prevent the cross-border spread of the virus. An alternative explanation for this result could be, for instance, that less globalised countries could close their borders more quickly because there was little resistance due to low cross-border traffic before the pandemic outbreak.[39]
d) When the country has lower government gross debt (Figure 17d[A]). Applying the assumption of an inverse relationship between government gross debt (interpreted as a country's budget constraint) and ERI to CCI, this result is also consistent with the assumption in Section 4.1.3. Containment and closure measures, such as stay-at-home requirements or

[36] It should be noted that this figure only applies to the respective institutional level, as the total number of cases varies by level.

[37] This does not necessarily imply that the respective institutions are irrelevant when deciding on government responses. Instead, there may be indirect effects that significantly increase the influence of other institutions.

[38] Another plausible explanation is that autocratic governments report embellished infection rates to the international community (Legiędź 2021: 594). Consequently, they may appear to be implementing more stringent measures when in fact, they may respond to an increase in COVID-19 cases.

[39] For a more detailed discussion, see, for example, Bickley et al. 2021.

restrictions on movement within the country, caused economic losses in various sectors of the economy, for example, the retail trade or the tourism sector. In particular, governments with comparatively low debt levels can compensate for the high costs.

e) When the country is less prepared to cope with a pandemic (Figure 17e[A]). This finding is also consistent with the corresponding assumption in Section 4.1.4. Decision-makers that governed a country with little capacity to cope with the pandemic were more decisive in implementing responses to avoid a collapse of the health system.

The next four ANOVAs with a binary dependent variable comprised of the results of the *all_econ* cluster analysis yield significant results with p-values below 0.05 only for three institutional variables: the unemployment rate (control variable at level 1), the Freedom in the World Index (level 2), and the number of medical doctors (level 4.2) (Table 4[A]). In addition, the effects of the Press Freedom Index (level 2) are examined, as this variable explains 2.1% of the variance in the response variable.[40] Again, most of the variance remains unexplained (Table 4[A]).

Next, boxplots are created for the above four institutional variables to assess why countries in cluster 1 responded more stringently until July 2020 and more softly thereafter, while countries in cluster 2 acted conversely (Figure 18[A]). The boxplots show that countries typically possess the following institutional characteristics when they have a higher ERI at the onset of the pandemic and a lower ERI later than would be expected with respect to COVID-19 cases:

a) More people are unemployed (Figure 18a[A]). This outcome contradicts the assumption in Section 4.1.4 that governments facing higher unemployment rates implement less stringent measures. However, as noted earlier, the effect can only be reasonably interpreted for the first month studied. In March 2020, both clusters have approximately the same mean in the *econ_updown_cases* dimension (Figure 4b). The result is thus not particularly meaningful.
b) The political system is more democratic (Figure 18b[A]). This finding could be explained by voters' preference for quick monetary support: Because elected politicians want to win the favour of their constituents, they adopt economic policy measures at the beginning of the pandemic that benefit many people. However, the longer the pandemic endures, the more intensely democracies debate new fiscal measures, as they meant higher debt.
c) The press is free (Figure 18c[A]). Complementing the result in b, lively debates in the free media about the need for rapid fiscal responses might have increased the speed with which economic policy measures were adopted (higher ERI). Several months after the onset of the pandemic, however, the media might have reflected the changing mood of the country, and policymakers might have delayed action (lower ERI).
d) There are relatively many medical doctors working in a country's healthcare system (Figure 18d[A]). In Section 4.1.4, no assumption was made about the effect of the number of

[40] It was found that the Press Freedom Index has a significant effect on the variation in government responses when an ANOVA is performed without the Freedom in the World Index (p-value of 0.003).

physicians in a country on its ERI. Therefore, the existence of a significant effect is somewhat surprising. One reason for this result could be that governments that spend more on their medical systems (and thus employ more physicians per 10,000 people) have higher priorities for investing in the well-being of their populations and thus want to ensure that in the short run, everyone has a decent standard of living. In the long run, countries with robust health systems may need to take fewer economic measures as fewer people become severely ill.

Finally, the four ANOVAs with the *all_health* cluster analysis results as the dependent variable show two significant results: p-values below 0.01 and 0.05, respectively, indicate that the group means of the survival versus self-expression values variable (level 1) and the Freedom in the World Index (level 2) are significantly different (Table 5[A]). These factors explain about 15% of the variance in the cluster analysis results at their respective institutional levels. Furthermore, the explanatory variable government gross debt (level 4.1) is examined more thoroughly. It explains about 3.6% of the variance in the assignment of countries to clusters 1 and 3 in the *all_health* cluster analysis. Again, much of the variance remains unexplained (Table 5[A]).

Boxplots for each of the above four explanatory variables indicate why countries in cluster 3 responded more stringently between May and July 2020 and more softly thereafter until September, while countries in cluster 1 responded conversely (Figure 19[A]). Countries in cluster 3 typically possess the following institutional features:

a) Self-expression values prevail (Figure 19a[A]). Interestingly, this finding partly contradicts the assumption in Section 4.1.1 that people who emphasise individual freedom are difficult to convince of stringent government responses. Two explanations are conceivable: First, in societies where self-expression values predominate, “an increasing share of the population has grown up taking survival [...] for granted” (Haerpfer et al. 2022b). Perhaps the unexpected emergence of a lethal virus shattered this certainty. Consequently, in the early months of the pandemic, even people guided by self-expression values likely demanded stringent measures. Second, these people value individual well-being (ibid.). Measures that improved personal welfare without severely restricting privacy (e.g., through testing policies or protection of the elderly) have been correspondingly less controversial.[41]

b) The political system is more democratic (Figure 19b[A]). The argument above regarding economic policy measures can also be applied here. Healthcare system measures probably enjoyed great popularity among voters at the onset of the pandemic. But the more regulations people had to follow, the more detailed they were debated in democracies.

c) The country has higher government gross debt (Figure 19c[A]). This outcome is inconsistent with the assumption in Section 4.1.3 that higher debt is associated with softer responses. One possible explanation could be that health system responses are less costly than

[41] For the average development of the *health_updown_dimension* after July 2020, the assumption from Section 4.1.4 applies again.

containment and closure measures or economic responses and are therefore preferred by countries with higher debt in an attempt to contain the pandemic early.

5. Conclusion

This thesis provides insight into the variation in government responses during the initial phase of the COVID-19 pandemic and seeks reasons in countries' institutional systems. Combined with studies of the effectiveness of government action in different countries and the respective long-term economic impacts, the results can shed light on which institutional systems are best prepared to cope with a pandemic.

Section 3.5 identified groups of countries that responded with similar stringency and roughly uniformly over time regarding containment and closure measures, economic, and health system responses. Interestingly, the mean trajectories showed opposite developments in several cases (e.g., in Figure 4). The ANOVAs reveal initial reasons for these differences, with a country's regime type being the most important driver. Other explanatory factors include the predominance of survival or self-expression values, the degree of globalisation, government gross debt, and a country's level of health security. The research question of whether institutional factors can explain differences in government responses to the COVID-19 pandemic is thus tentatively confirmed. Yet, other institutional variables, such as government spending, level of inequality, or access to sanitation, do not show significant effects.

Since much of the variation remains unexplained, future research is needed that incorporates other (control) variables in the analysis that could not be considered in this thesis due to its scope. These include, for instance, the age distribution of the population, since "[o]lder adults [...] are at particular risk of having severe infection and are at higher risk of dying as a result of the disease" (Lithander et al. 2020: 502), and seasonality, as "COVID-19 infectivity and mortality of SARS-CoV-2 are both stronger in colder climates" (Liu et al. 2021: 9). Moreover, expectations about macroeconomic impact likely influenced governments' decisions about appropriate responses. For example, future research could include variables on the share of workers in the industrial sector, where remote work is rare, and the proportion of workers in the service sector. In addition, it remains unclear why, for instance, the mean trajectories without the outlier clusters of the *all_econ* cluster analysis show a reverse development starting in July of all months (Figure 4).

Finally, conducting a (k-means) cluster analysis is only the first step to identifying patterns among government responses (see 3.1). To confirm the existence of the identified clusters, future studies should use hierarchical clustering methods (or in combination with KML) and investigate the consistency of the results (Backhaus et al. 2018: 530f.; Teuling et al. 2021: 25).

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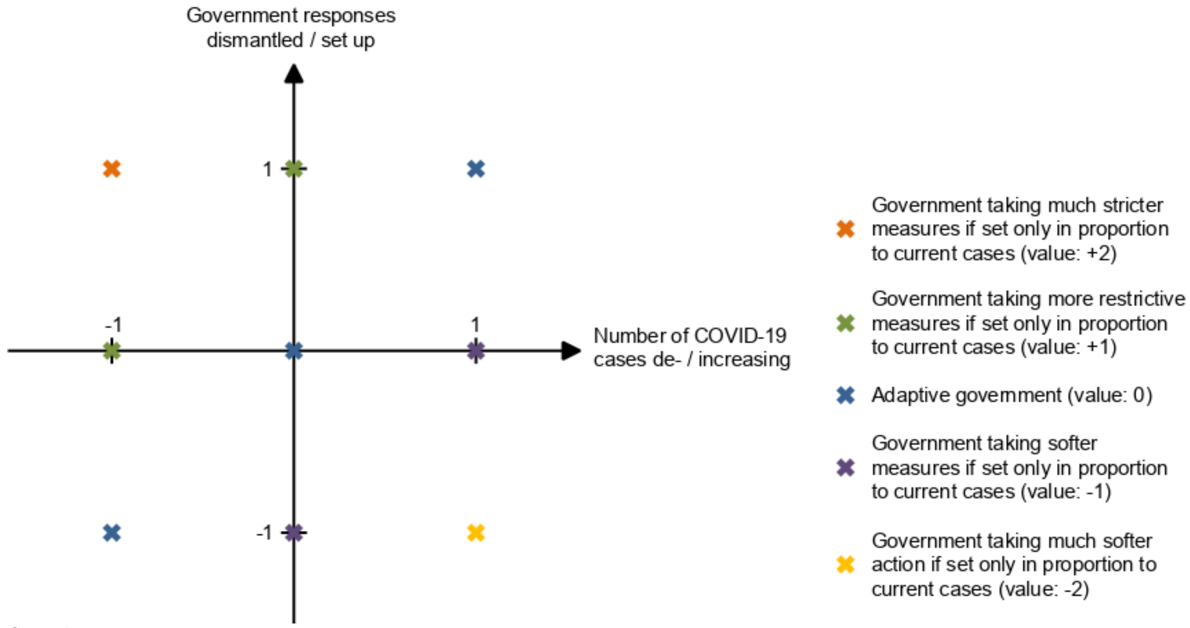
Appendix

A. Figures and Tables

Figure 6 – Fourth, fifth, and sixth dimensions: relationship between a change in CCI/ERI/HSI and COVID-19 cases



(Own figure)

Figure 7 – Correlation matrix across all dimensions

	econ_cases	health_cases	conclos_updown_cases	econ_updown_cases	health_updown_cases
econ_updown_cases					0.651
conclos_updown_cases				0.626	0.63
health_cases			-0.117	-0.103	-0.156
econ_cases		0.049	-0.059	-0.082	-0.071
conclos_cases	0.229	0.113	0.013	0.021	0.013

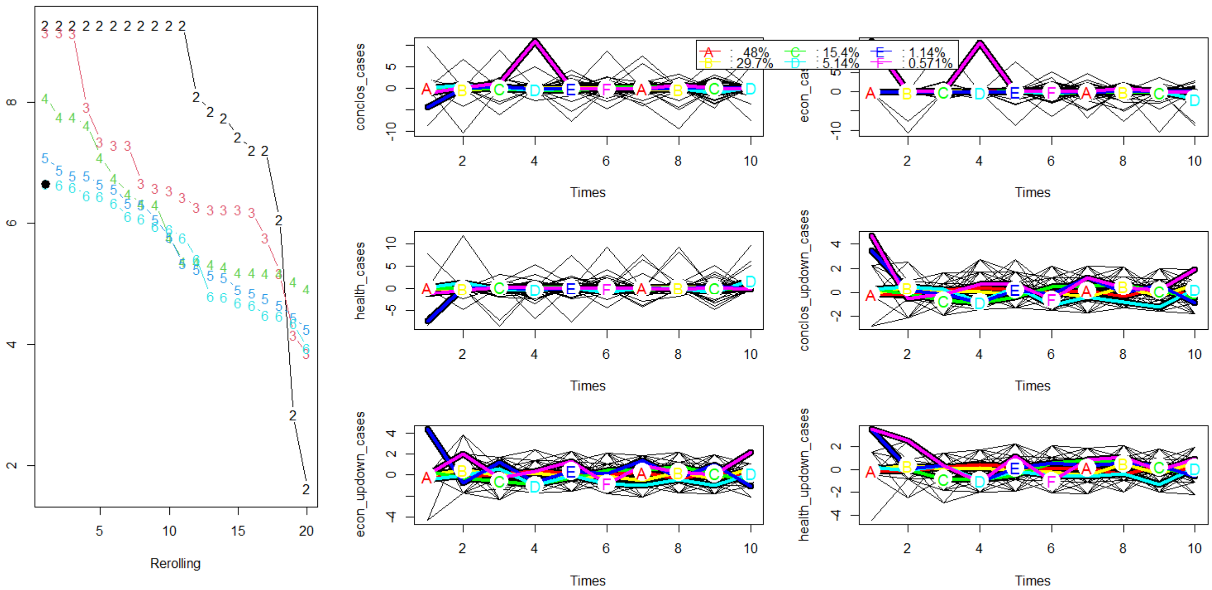
(Own figure based on calculations with data from the OxCGRT database (see 3.2). For information on the six dimensions, see Section 3.3. The correlations between the dimensions are examined because variables used in a cluster analysis should not be highly correlated (see 3.3). Figures highlighted with a circle indicate a correlation greater than 0.5. From the diagram, it is evident that the fourth, fifth, and sixth dimensions are highly positively correlated with each other. Accordingly, the cluster analysis, which includes all six dimensions, should be interpreted with caution.)

Table 1 – Summary of the output of all cluster analyses

	Clustering *all*	Clustering *conclos*	Clustering *econ*	Clustering *health*
No. of clusters	**6**	**6**	**4**	**5**
C1 (no. of countries)	48.00% (84)	23.43% (41)	66.28% (116)	37.14% (65)
C2 (no. of countries)	29.71% (52)	21.14% (37)	31.43% (55)	30.86% (54)
C3 (no. of countries)	15.43% (27)	18.86% (33)	1.71% (3)	30.29% (53)
C4 (no. of countries)	5.14% (9)	17.71% (31)	0.57% (1)	1.14% (2)
C5 (no. of countries)	1.14% (2)	17.14% (30)	-	0.57% (1)
C6 (no. of countries)	0.57% (1)	1.71% (3)	-	-
Calinski.Harabasz	6.653	8.384	14.241	9.891
Calinski.Harabasz2	0.203	0.255	0.254	0.238
Calinski.Harabasz3	14.877	18.746	24.665	19.782
Ray.Turi	-0.082	-0.126	-0.179	-0.163
Davies.Bouldin	-1.60	-1.770	-1.457	-1.398
BIC	-30182.095	-10295.546	-9773.777	-10062.137
BIC2	-31660.153	-10658.030	-10016.432	-10364.706
AIC	-29039.607	-9912.607	-9517.430	-9742.493
AICc	-27641.939	-10469.664	-9660.268	-10024.740
AICc2	-29065.388	-9921.347	-9521.316	-9748.557
postProbaGlobal	0.952	0.845	0.878	0.838
random	-0.521	0.435	1.239	1.097

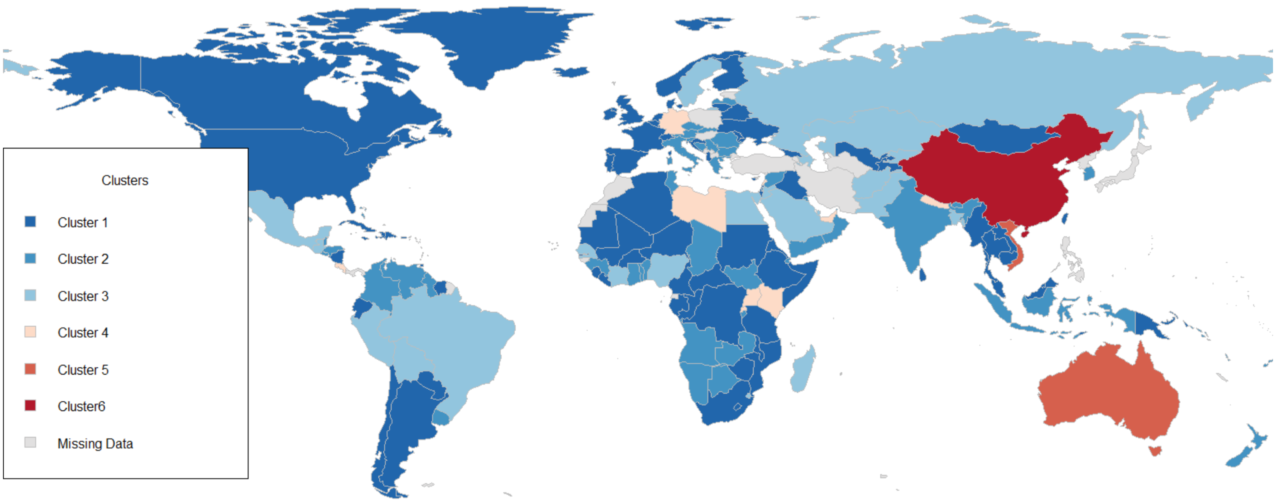
(Own figure based on calculations with data from the OxCGRT database (see 3.2). A k-means cluster analysis for joint longitudinal data is performed four times for all 175 countries and ten time points (see 3.1 and 3.4). The analyses differ in their input variables. The first cluster analysis (column 'Clustering all') includes all six dimensions: conclos_cases, conclos_updown_cases, econ_cases, econ_updown_cases, health_cases, and health_updown_cases (for the six dimensions, see Section 3.3). In the second cluster analysis (column 'Clustering conclos'), only the two 'conclos' dimensions are inputted. Meanwhile, the third and fourth cluster analyses (columns 'Clustering econ' and 'Clustering health') are based on the data of the 'econ' and 'health' dimensions, respectively. The table summarises the output for the selected partition (see Section 3.4 for selection criteria). Below the number of clusters in the final partition is indicated how many cases (i.e., countries) are assigned to each cluster in percent. The number in parentheses shows the absolute number of countries per cluster. Moreover, the values of several quality criteria for the final partition are given.)

Figure 8 – kml3d() results for all dimensions



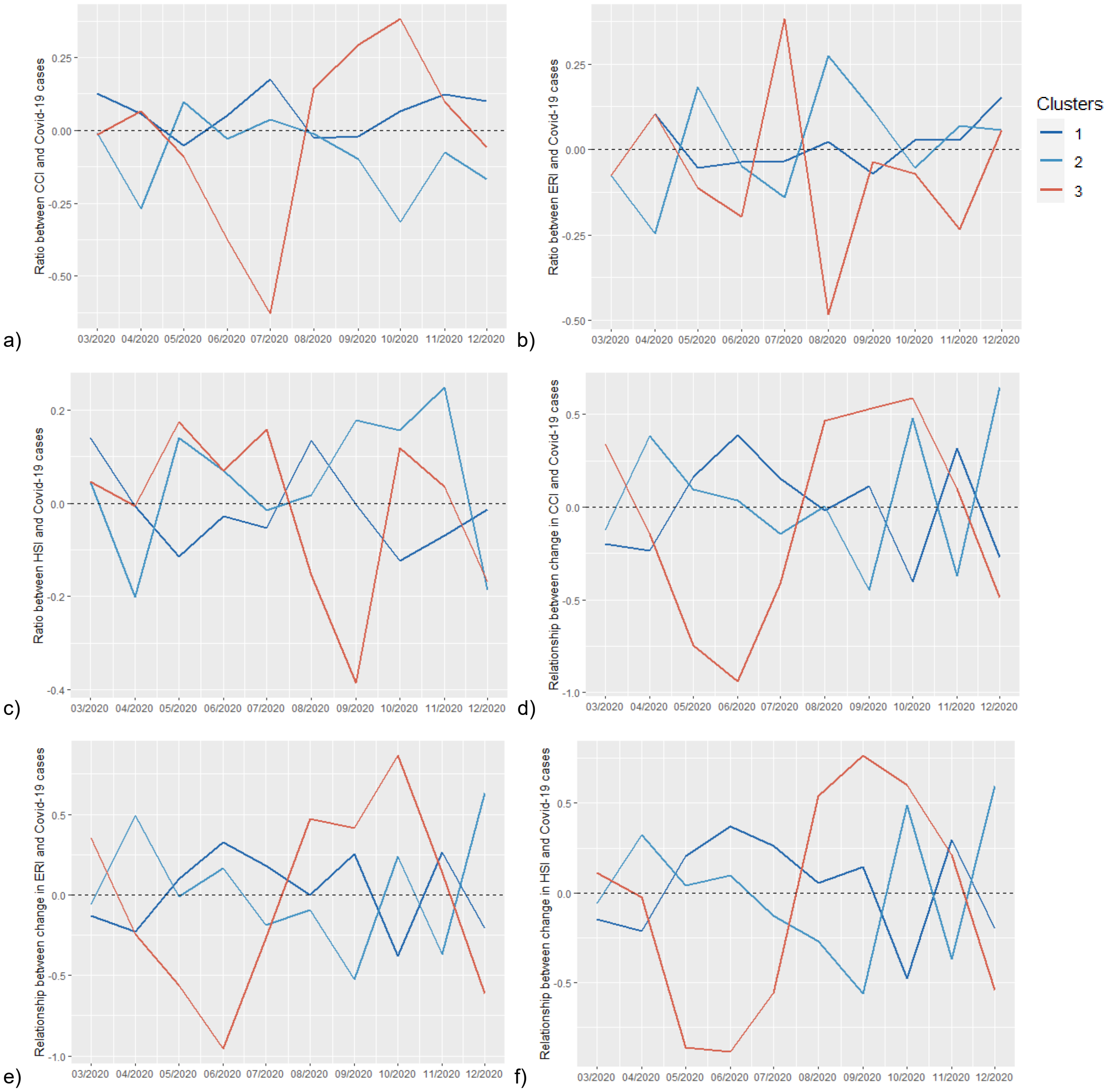
(Own figure based on calculations with data from the OxCGRT database (see 3.2). For information on the dimensions, see Section 3.3. A k-means cluster analysis for joint longitudinal data (see 3.1) is performed in R with the kml3d() function (see 3.4). The chart on the left shows the value of a quality criterion for all partitions found. The Calinski and Harabasz criterion appears first by default. The partitions are represented by their respective numbers of clusters. Here, the partition with six clusters (A–F) is selected, marked by the black dot. For selection criteria, see Section 3.4. On the right side, the mean trajectories of the selected partition are displayed. The x-axis shows the ten time points of the data, i.e., the first day of each month between March (= 1) and December 2020 (= 10).)

Figure 9 – World map of cluster analysis results including all dimensions



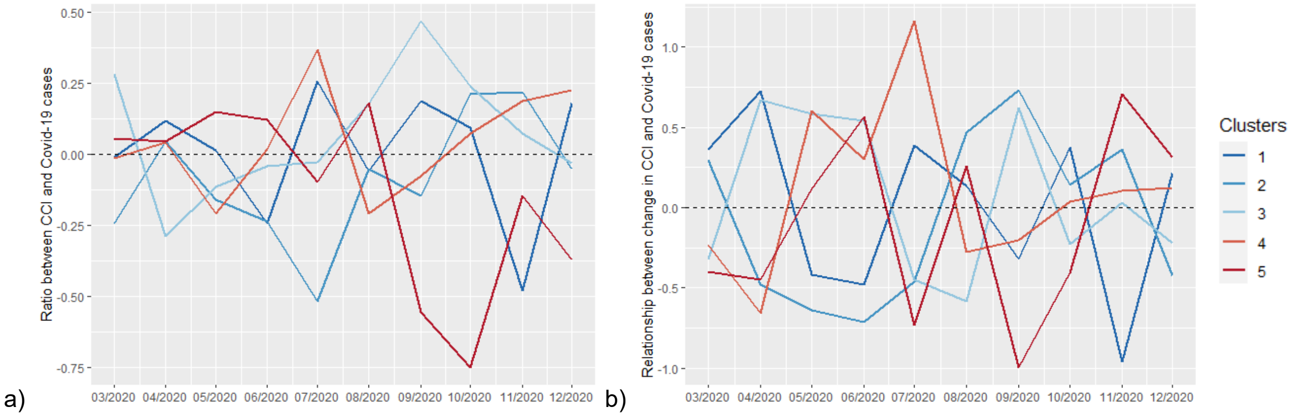
(Own figure based on the results of a k-means cluster analysis for joint longitudinal data (see 3.1 and 3.4) with six dimensions (see 3.3), which are calculated using data from the OxCGRT database (see 3.2). The results are plotted on the world map using the rworldmap package in R.)

Figure 10 – Mean trajectories without outlier clusters of the *all_all* cluster analysis



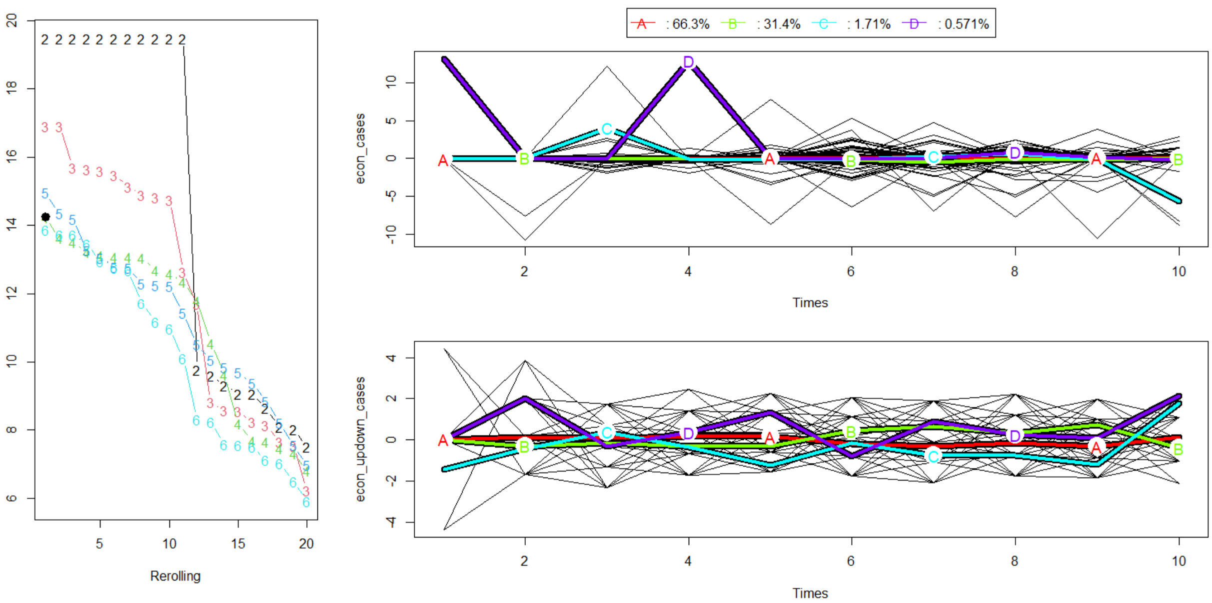
(Own figure based on the results of a k-means cluster analysis for joint longitudinal data (see 3.1 and 3.4) with six dimensions (see 3.3), calculated using data from the OxCGRT database (see 3.2). The selected partition includes six clusters, but three contain only a small number of cases. To examine the differences between the larger clusters in more detail, their means are plotted again without the outlier clusters. Graph a displays changes in the conclos_cases dimension, graph b shows developments in the conclos_updown_cases dimension, and graphs c, d, e, and f plot trends in the econ_cases, econ_updown_cases, health_cases, and health_updown_cases dimensions, respectively. The data are z-score standardised.)

Figure 11 – Mean trajectories without outlier clusters of the *all_conclos* cluster analysis



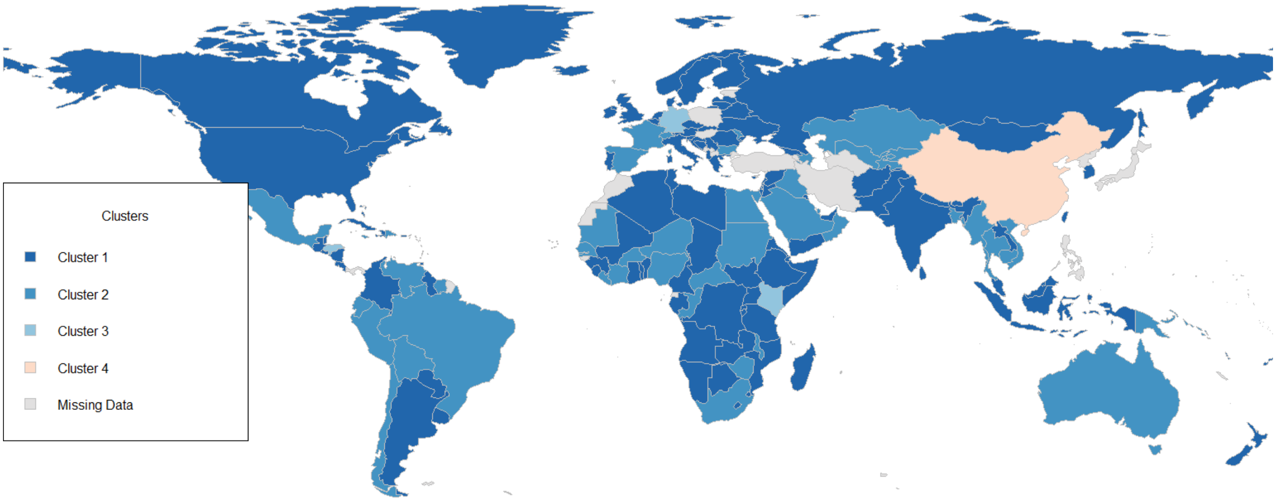
(Own figure based on the results of a k-means cluster analysis for joint longitudinal data (see 3.1 and 3.4) with the dimensions conclos_cases and conclos_updown_cases (see 3.3), which are calculated using data from the OxCGRT database (see 3.2). The selected partition includes six clusters, but one contains only a small number of cases. To examine the differences between the larger clusters in more detail, their means are plotted again without the outlier cluster. Graph a displays changes in the conclos_cases dimension, while graph b shows trends in the conclos_updown_cases dimension. The data are z-score standardised.)

Figure 12 – kml3d() results for the *econ_cases* and *econ_updown_cases* dimensions



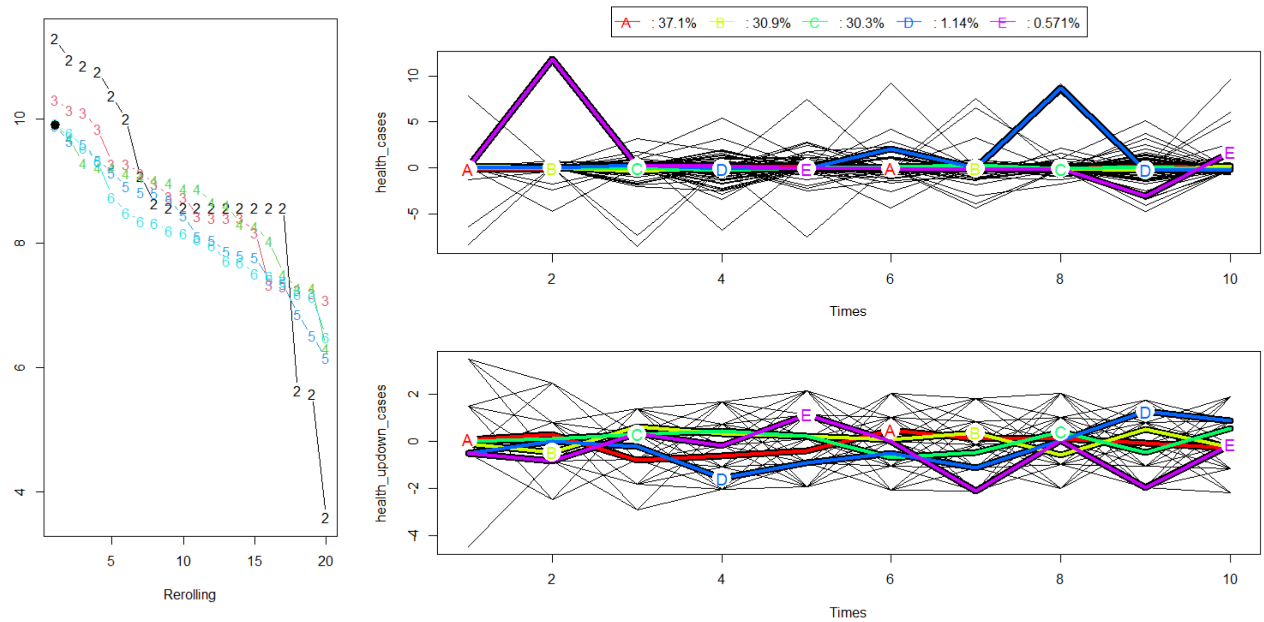
(Own figure based on calculations with data from the OxCGRT database (see 3.2). For information on the dimensions, see Section 3.3. A k-means cluster analysis for joint longitudinal data (see 3.1) is performed in R with the kml3d() function (see 3.4). The chart on the left shows the value of a quality criterion for all partitions found. The Calinski and Harabasz criterion appears first by default. The partitions are represented by their respective numbers of clusters. Here, the partition with four clusters (A–D) is selected, marked by the black dot. For selection criteria, see Section 3.4. On the right side, the mean trajectories of the selected partition are displayed. The x-axis shows the ten time points of the data, i.e., the first day of each month between March (= 1) and December 2020 (= 10).)

Figure 13 – World map of cluster analysis results including only ERI dimensions



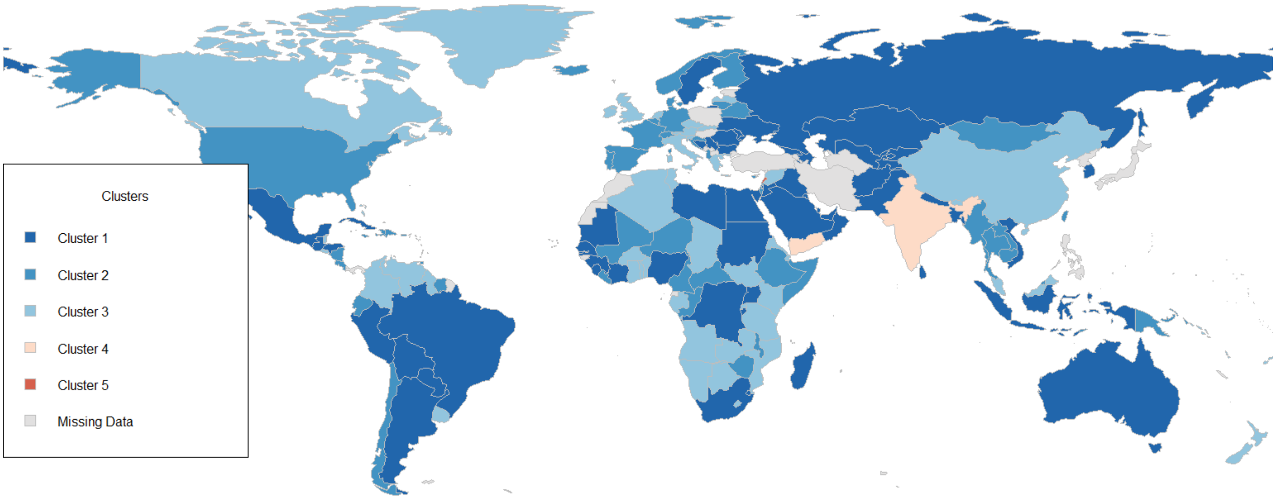
(Own figure based on the results of a k-means cluster analysis for joint longitudinal data (see 3.1 and 3.4) with the dimensions econ_cases and econ_updown_cases (see 3.3), which are calculated using data from the OxCGRT database (see 3.2). The results are plotted on the world map using the rworldmap package in R.)

Figure 14 – kml3d() results for the *health_cases* and *health_updown_cases* dimensions



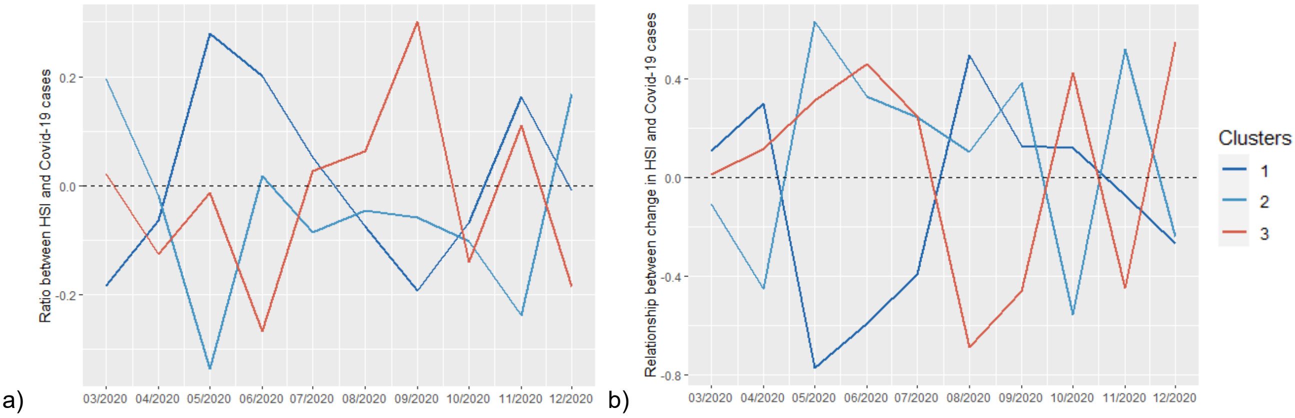
(Own figure based on calculations with data from the OxCGRT database (see 3.2). For information on the dimensions, see Section 3.3. A k-means cluster analysis for joint longitudinal data (see 3.1) is performed in R with the kml3d() function (see 3.4). The chart on the left shows the value of a quality criterion for all partitions found. The Calinski and Harabasz criterion appears first by default. The partitions are represented by their respective numbers of clusters. Here, the partition with five clusters (A–E) is selected, marked by the black dot. For selection criteria, see Section 3.4. On the right side, the mean trajectories of the selected partition are displayed. The x-axis shows the ten time points of the data, i.e., the first day of each month between March (= 1) and December 2020 (= 10).)

Figure 15 – World map of cluster analysis results including only HSI dimensions



(Own figure based on the results of a k-means cluster analysis for joint longitudinal data (see 3.1 and 3.4) with the dimensions health_cases and health_updown_cases (see 3.3), which are calculated using data from the OxCGRT database (see 3.2). The results are plotted on the world map using the rworldmap package in R.)

Figure 16 – Mean trajectories without outlier clusters of the *all_health* cluster analysis



(Own figure based on the results of a k-means cluster analysis for joint longitudinal data (see 3.1 and 3.4) with the dimensions health_cases and health_updown_cases (see 3.3), which are calculated using data from the OxCGRT database (see 3.2). The selected partition includes six clusters, but one contains only a small number of cases. To examine the differences between the larger clusters in more detail, their means are plotted again without the outlier clusters. Graph a displays changes in the health_cases dimension, while graph b shows trends in the health_updown_cases dimension. The data are z-score standardised.)

Table 2 – Summary statistics of institutional variables

Indicator	*Year(s)*	*Scale / Unit*	*N*	*Mean*	*SD*	*Min*	*Max*	*Source*
Level 1: Social Embeddedness								
Government's versus individual's responsibility to ensure that everyone is provided for	2017–2022	1 to 10 (10: individual responsibility)	50	5.00	0.95	2.54	7.89	Haerpfer et al. 2022e
Traditional versus secular-rational values	2017–2022	Positive score: mainly secular-rational values	50	-0.42	0.93	-1.76	1.47	Haerpfer et al. 2022a[42]
Survival versus self-expression values	2017–2022	Positive score: mainly self-expression values	50	-0.14	1.06	-2.23	2.88	Haerpfer et al. 2022a[42]
Level 2: Institutional Environment								
Freedom in the World Index	2019	0 to 100 (100: free country)	116	63.32	27.76	7	100	Freedom House 2022
Press Freedom Index	2019	0 to 100 (100: free press)	116	68.94	10.16	27.55	92.18	RSF 2021a
State expenses	2012–2019	in % of GDP	116	25.41	13.10	0.00	49.14	The World Bank 2022a
Level 4.1: Resource Allocation in the Economic System								
KOF Globalisation Index, de facto	2019	0 to 100 (100: high degree of globalisation)	126	61.60	14.97	29.61	90.38	Gygli et al. 2022b
General government gross debt	2019	in % of GDP	126	58.64	31.58	7.95	200.35	IMF 2022
Relative poverty line (Population living in households with an income or expenditure per person below 50% of the median)	2010–2019	in % of total population	126	12.86	5.13	3.49	25.26	Hasell/Arriagada 2023

[42] Data are "based on the latest joint survey round of the World Values Survey and European Values Study 2017–2022" (Haerpfer et al. 2022c).

Indicator	*Year(s)*	*Scale / Unit*	*N*	*Mean*	*SD*	*Min*	*Max*	*Source*
Level 4.2: Resource Allocation in the Health System								
Population using at least basic sanitation services	2016–2019	in % of total population	101	81.10	27.47	8.63	100	WHO 2021a
Population using safely managed sanitation services	2016–2019	in % of total population	101	58.41	30.02	6.48	100	WHO 2021b
Number of medical doctors	2013–2019	per 10,000 people	101	23.73	18.22	0.23	84.2	WHO 2022a
Global Health Security Index	2019	0 to 100 (100: most favourable health security conditions)	101	44.54	14.33	17.9	76.2	NTI et al. 2021a
Control variables								
GDP per capita	2011–2019	in current US$	162	15599	21286.29	217	112622	The World Bank 2022b
Unemployment rate	2019	in % of total labour force	162	7.02	5.64	0.1	28.47	The World Bank 2022c

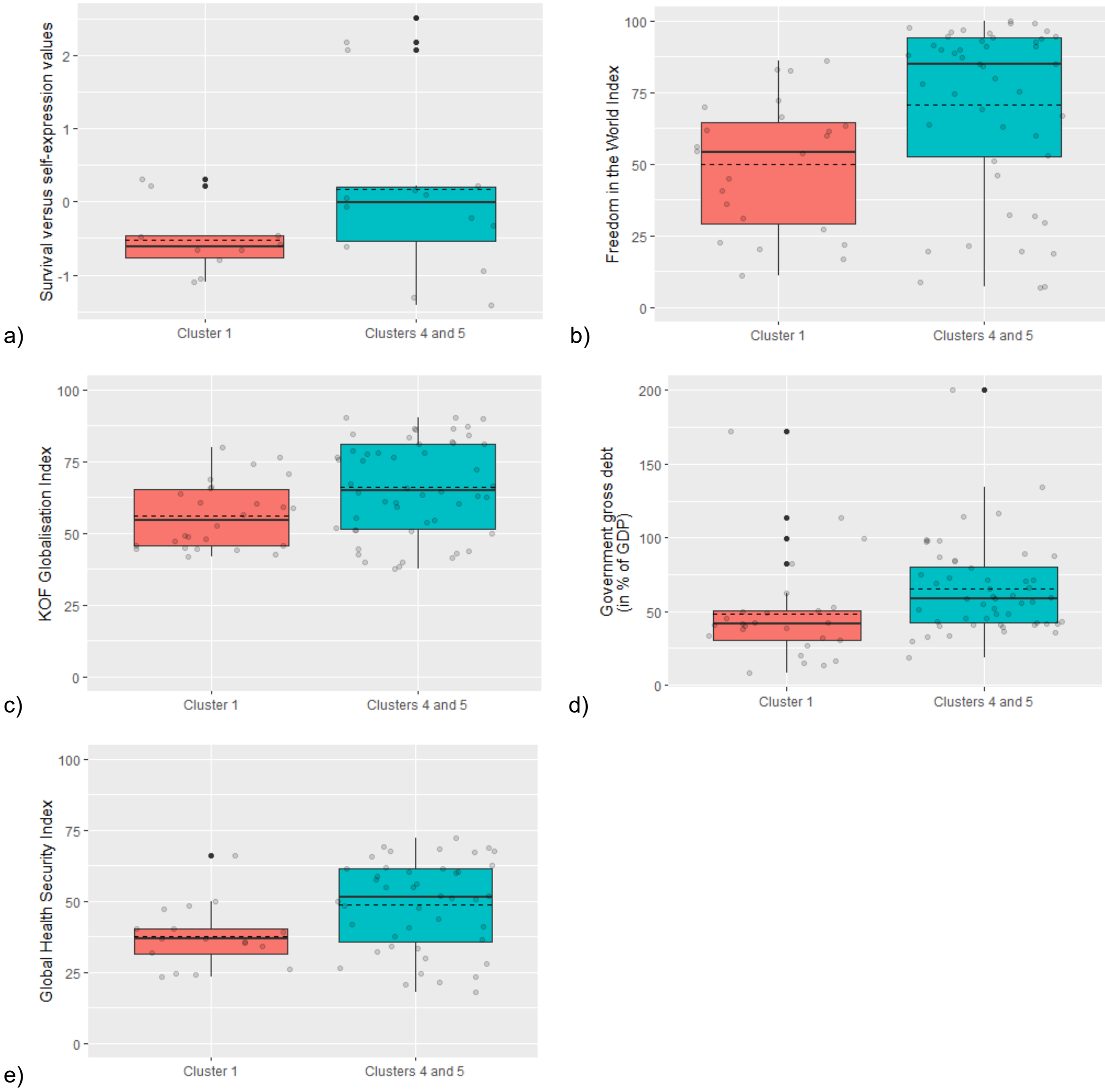
(Own figure; Institutional variables are selected and classified according to Williamson's typology presented in Section 2. For more information on the variables, see Section 4.1. When a time series is available (see Column 2), the most recent value between 2010 and 2019 is chosen. Data older than 13 years are considered too imprecise. For more recent data (from 2020–2023), there is a possibility that the aftermath of the COVID-19 pandemic significantly altered the institutions. However, this effect is not of interest in this thesis. Only the data from the WVS do not meet these criteria, as "about a dozen of countries [conducted] their fieldwork since the pandemic outbreak" (Haerpfer et al. 2022f). The variables of each institutional level are each combined into a separate dataset, to which the two control variables are added. Rows with missing data are deleted from all datasets to simplify the subsequent analysis. Therefore, the total number of cases (N) within a dataset is the same. This table contains summary statistics of the final datasets.)

Table 3 – Results of ANOVA for Clustering *conclos*

Level 1: Social Embeddedness	**Df**	**Sum Sq**	**Mean Sq**	**F value**	**Pr(>F)**	**η^2**
Government's vs individual's responsibility to ensure that everyone is provided for	1	0.376	0.376	1.678	0.212	0.064
Traditional vs secular-rational values	1	0.319	0.319	1.423	0.248	0.055
Survival vs self-expression values	1	0.623	0.623	2.782	0.113	0.107
GDP per capita	1	0.463	0.463	2.069	0.167	0.079
Unemployment rate	1	0.023	0.023	0.105	0.750	0.004
Residuals	*18*	*4.030*	*0.224*			
Level 2: Institutional Environment	**Df**	**Sum Sq**	**Mean Sq**	**F value**	**Pr(>F)**	**η^2**
Freedom in the World Index	1	1.755	1.755	8.671	0.004 **	0.113
Press Freedom Index	1	0.042	0.042	0.209	0.649	0.003
State expenses	1	0.001	0.001	0.003	0.956	0.000
GDP per capita	1	0.473	0.473	2.336	0.131	0.030
Unemployment rate	1	0.119	0.119	0.590	0.445	0.008
Residuals	*65*	*13.159*	*0.202*			
Level 4.1: Resource Allocation in the Economic System	**Df**	**Sum Sq**	**Mean Sq**	**F value**	**Pr(>F)**	**η^2**
KOF Globalisation Index, de facto	1	1.550	1.550	7.642	0.007 **	0.089
General government gross debt	1	0.815	0.815	4.019	0.049 *	0.047
Relative poverty line	1	0.055	0.055	0.272	0.603	0.003
GDP per capita	1	0.296	0.296	1.458	0.231	0.017
Unemployment rate	1	0.017	0.017	0.085	0.771	0.001
Residuals	*72*	*14.601*	*0.203*			
Level 4.2: Resource Allocation in the Health System	**Df**	**Sum Sq**	**Mean Sq**	**F value**	**Pr(>F)**	**η^2**
Population using at least basic sanitation services	1	0.402	0.402	2.095	0.154	0.033
Population using safely managed sanitation services	1	0.056	0.056	0.293	0.590	0.005
Medical doctors per 10,000 people	1	0.000	0.000	0.002	0.968	0.000
Global Health Security Index	1	1.298	1.298	6.759	0.012 *	0.106
GDP per capita	1	0.064	0.064	0.331	0.568	0.005
Unemployment rate	1	0.075	0.075	0.392	0.534	0.006
Residuals	*54*	*10.367*	*0.192*			

*(Own figure based on the results of the all_conclos cluster analysis discussed in Section 3.5. Four ANOVAs (see 4.3) are performed to determine whether differences in institutions can explain some of the variation in government responses. A binary variable indicating a country's assignment to a cluster is entered as the dependent variable, coded 0 for countries in cluster 1 and 1 for countries in clusters 4 and 5. Clusters 2, 3, and 6 are excluded from the analysis. For information on the selection of explanatory variables, see Section 4.1. The unemployment rate and GDP per capita serve as control variables (see 4.1.5). Due to the scope of this thesis, no interaction effects are considered. The table summarises the results of the ANOVAs. The rows labelled 'Residuals' provide information about the variation in the response variable that cannot be explained by the institutional variables. Next to the column Pr(>F), which contains the p-value, asterisks indicate the significance level: ** for $p < 0.01$ and * for $p < 0.05$. Moreover, eta squared (η^2) is calculated. It "measures the proportion of the variation in [the dependent variable] that is associated with membership of the different groups defined by [the independent variable]" (Richardson 2011: 136).)*

Figure 17 – Boxplots for selected results of *all_conclos* ANOVAs



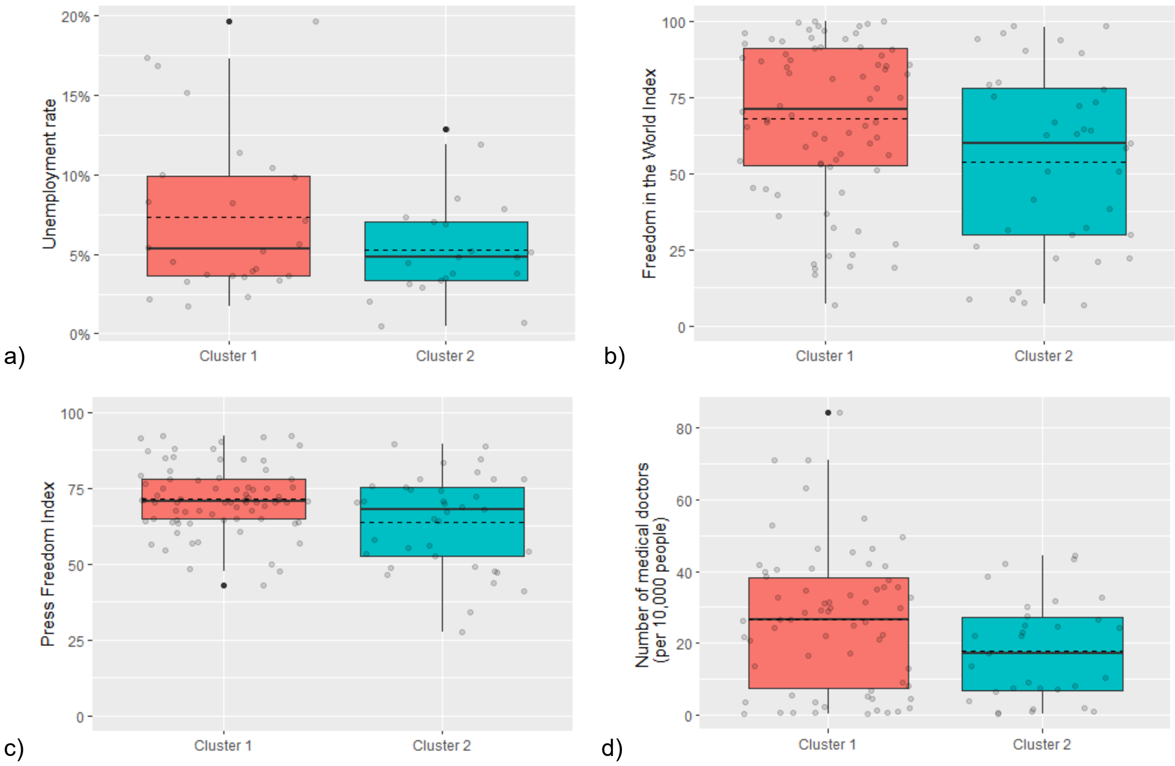
(Own figure based on the results of the all_conclos cluster analysis discussed in Section 3.5. After running four ANOVAs (see 4.3), selected results are plotted to further assess how institutional differences may explain the fact that countries in cluster 1 responded more stringently in March and April 2020, while countries in clusters 4 and 5 responded more softly (as measured by the conclos_updown_cases dimension, see 3.3). Information on the institutional variables plotted on the y-axes, namely (a) survival versus self-expression values, (b) the Freedom in the World Index, (c) the KOF Globalisation Index, (d) government gross debt, and (e) the Global Health Security Index, is given in Section 4.1. Since the variables are coded and scaled differently (see Table 2[A]), the y-axes have different scaling. Moreover, it should be noted that R does not control for other institutional variables when drawing the boxplots. The dashed lines in the boxplots indicate means, while the solid lines represent the respective medians.)

Table 4 – Results of ANOVA for Clustering *econ*

Level 1: Social Embeddedness	**Df**	**Sum Sq**	**Mean Sq**	**F value**	**Pr(>F)**		**η^2**
Government's vs individual's responsibility to ensure that everyone is provided for	1	0.010	0.010	0.043	0.837		0.001
Traditional vs secular-rational values	1	0.139	0.139	0.574	0.453		0.012
Survival vs self-expression values	1	0.331	0.331	1.362	0.250		0.028
GDP per capita	1	0.003	0.003	0.011	0.916		0.000
Unemployment rate	1	1.175	1.175	4.839	0.034	*	0.101
Residuals	*41*	*9.958*	*0.243*				
Level 2: Institutional Environment	**Df**	**Sum Sq**	**Mean Sq**	**F value**	**Pr(>F)**		**η^2**
Freedom in the World Index	1	1.401	1.401	6.666	0.011	*	0.056
Press Freedom Index	1	0.531	0.531	2.526	0.115		0.021
State expenses	1	0.214	0.214	1.016	0.316		0.009
GDP per capita	1	0.247	0.247	1.173	0.281		0.010
Unemployment rate	1	0.004	0.004	0.019	0.889		0.000
Residuals	*107*	*22.489*	*0.210*				
Level 4.1: Resource Allocation in the Economic System	**Df**	**Sum Sq**	**Mean Sq**	**F value**	**Pr(>F)**		**η^2**
KOF Globalisation Index, de facto	1	0.430	0.430	1.952	0.165		0.016
General government gross debt	1	0.081	0.081	0.368	0.546		0.003
Relative poverty line	1	0.053	0.053	0.243	0.623		0.002
GDP per capita	1	0.005	0.005	0.024	0.876		0.000
Unemployment rate	1	0.041	0.041	0.186	0.667		0.002
Residuals	*116*	*25.553*	*0.220*				
Level 4.2: Resource Allocation in the Health System	**Df**	**Sum Sq**	**Mean Sq**	**F value**	**Pr(>F)**		**η^2**
Population using at least basic sanitation services	1	0.031	0.031	0.145	0.704		0.002
Population using safely managed sanitation services	1	0.195	0.195	0.926	0.338		0.010
Medical doctors per 10,000 people	1	1.253	1.253	5.958	0.017	*	0.065
Global Health Security Index	1	0.050	0.050	0.235	0.629		0.003
GDP per capita	1	0.113	0.113	0.538	0.465		0.006
Unemployment rate	1	0.409	0.409	1.944	0.167		0.021
Residuals	*91*	*19.144*	*0.210*				

*(Own figure based on the results of the all_econ cluster analysis discussed in Section 3.5. Four ANOVAs (see 4.3) are performed to determine whether differences in institutions can explain some of the variation in government responses. A binary variable indicating a country's assignment to a cluster is entered as the dependent variable, coded 0 for countries in cluster 1 and 1 for countries in cluster 2. Clusters 3 and 4 are excluded due to their small number of cases. For information on the selection of explanatory variables, see Section 4.1. The unemployment rate and GDP per capita serve as control variables (see 4.1.5). Due to the scope of this thesis, no interaction effects are considered. The table summarises the results of the ANOVAs. The rows labelled 'Residuals' provide information about the variation in the response variable that cannot be explained by the institutional variables. Next to the column Pr(>F), which contains the p-value, asterisks indicate the significance level: ** for $p < 0.01$ and * for $p < 0.05$. Moreover, eta squared (η^2) is calculated. It "measures the proportion of the variation in [the dependent variable] that is associated with membership of the different groups defined by [the independent variable]" (Richardson 2011: 136).)*

Figure 18 – Boxplots for selected results of *all_econ* ANOVAs



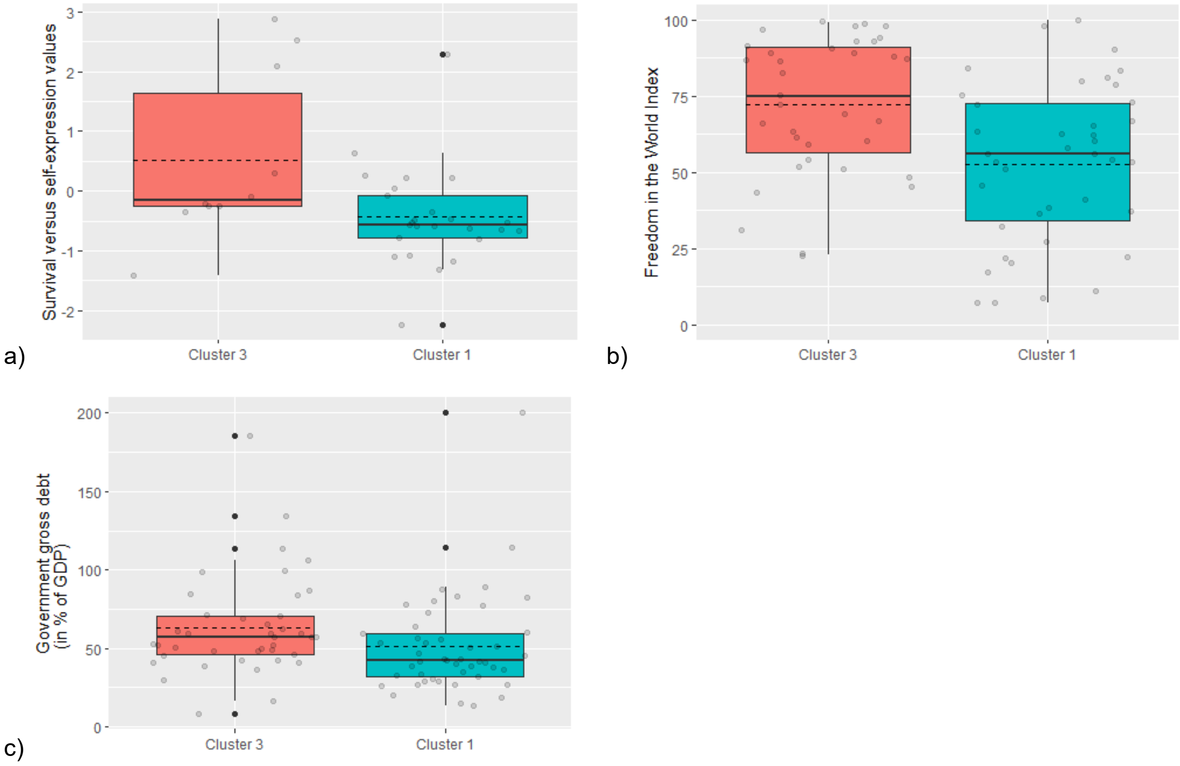
(Own figure based on the results of the all_econ cluster analysis discussed in Section 3.5. After running four ANOVAs (see 4.3), selected results are plotted to further assess how institutional differences may explain the fact that countries in cluster 1 responded more stringently until July 2020 and more softly thereafter, while countries in cluster 2 acted conversely (as measured by the econ_updown_cases dimension, see 3.3). Information on the institutional variables plotted on the y-axes, namely (a) the unemployment rate, (b) the Freedom in the World Index, (c) the Press Freedom Index, and (d) the number of medical doctors, is given in Section 4.1. Since the variables are coded and scaled differently (see Table 2^{A}), the y-axes have different scaling. Moreover, it should be noted that R does not control for other institutional variables when drawing the boxplots. The dashed lines in the boxplots indicate means, while the solid lines represent the respective medians.)

Table 5 – Results of ANOVA for Clustering *health*

Level 1: Social Embeddedness	**Df**	**Sum Sq**	**Mean Sq**	**F value**	**Pr(>F)**		**η^2**
Government's vs individual's responsibility to ensure that everyone is provided for	1	0.029	0.029	0.153	0.699		0.004
Traditional vs secular-rational values	1	0.014	0.014	0.073	0.789		0.002
Survival vs self-expression values	1	1.139	1.139	5.965	0.021	*	0.160
GDP per capita	1	0.126	0.126	0.659	0.423		0.018
Unemployment rate	1	0.295	0.295	1.545	0.224		0.041
Residuals	*29*	*5.539*	*0.191*				
Level 2: Institutional Environment	**Df**	**Sum Sq**	**Mean Sq**	**F value**	**Pr(>F)**		**η^2**
Freedom in the World Index	1	2.587	2.587	11.589	0.001	**	0.140
Press Freedom Index	1	0.613	0.613	2.745	0.102		0.033
State expenses	1	0.062	0.062	0.277	0.600		0.003
GDP per capita	1	0.002	0.002	0.007	0.935		0.000
Unemployment rate	1	0.000	0.000	0.001	0.970		0.000
Residuals	*68*	*15.182*	*0.223*				
Level 4.1: Resource Allocation in the Economic System	**Df**	**Sum Sq**	**Mean Sq**	**F value**	**Pr(>F)**		**η^2**
KOF Globalisation Index, de facto	1	0.334	0.334	1.375	0.244		0.015
General government gross debt	1	0.772	0.772	3.183	0.078		0.036
Relative poverty line	1	0.230	0.230	0.948	0.333		0.011
GDP per capita	1	0.617	0.617	2.544	0.115		0.029
Unemployment rate	1	0.009	0.009	0.036	0.851		0.000
Residuals	*81*	*19.648*	*0.243*				
Level 4.2: Resource Allocation in the Health System	**Df**	**Sum Sq**	**Mean Sq**	**F value**	**Pr(>F)**		**η^2**
Population using at least basic sanitation services	1	0.190	0.190	0.799	0.375		0.012
Population using safely managed sanitation services	1	0.235	0.235	0.989	0.324		0.015
Medical doctors per 10,000 people	1	0.037	0.037	0.155	0.695		0.002
Global Health Security Index	1	0.455	0.455	1.911	0.172		0.029
GDP per capita	1	0.535	0.535	2.247	0.139		0.035
Unemployment rate	1	0.423	0.423	1.776	0.188		0.027
Residuals	*57*	*13.563*	*0.238*				

*(Own figure based on the results of the all_health cluster analysis discussed in Section 3.5. Four ANOVAs (see 4.3) are performed to determine whether differences in institutions can explain some of the variation in government responses. A binary variable indicating a country's assignment to a cluster is entered as the dependent variable, coded 0 for countries in cluster 3 and 1 for countries in cluster 1. Clusters 2, 4, and 5 are excluded from the analysis. For information on the selection of explanatory variables, see Section 4.1. The unemployment rate and GDP per capita serve as control variables (see 4.1.5). Due to the scope of this thesis, no interaction effects are considered. The table summarises the results of the ANOVAs. The rows labelled 'Residuals' provide information about the variation in the response variable that cannot be explained by the institutional variables. Next to the column Pr(>F), which contains the p-value, asterisks indicate the significance level: ** for $p < 0.01$ and * for $p < 0.05$. Moreover, eta squared (η^2) is calculated. It "measures the proportion of the variation in [the dependent variable] that is associated with membership of the different groups defined by [the independent variable]" (Richardson 2011: 136).)*

Figure 19 – Boxplots for selected results of *all_health* ANOVAs



(Own figure based on the results of the all_health cluster analysis discussed in Section 3.5. After running four ANOVAs (see 4.3), selected results are plotted to further assess how institutional differences may explain the fact that countries in cluster 3 responded more stringently between May and July 2020 and more softly thereafter until September, while countries in cluster 1 acted conversely (as measured by the health_updown_cases dimension, see 3.3). Information on the institutional variables plotted on the y-axes, namely (a) survival versus self-expression values, (b) the Freedom in the World Index, and (c) government gross debt, is given in Section 4.1. Since the variables are coded and scaled differently (see Table 2^{A}), the y-axes have different scaling. Moreover, it should be noted that R does not control for other institutional variables when drawing the boxplots. The dashed lines in the boxplots indicate means, while the solid lines represent the respective medians.)

B. Index calculation

Table 6 lists all variables that are used to calculate the three indices CCI, ERI, and HSI. The classification has been slightly modified from Hale et al. (2021: 530). The indices are mutually exclusive. For 12 ordinal scaled variables, additional information about their scope is included in the form of binary flag variables. Most of these flags (for variables C1 through C7, H1, H6, and H8) relate to geographic scope. They are included because the policies may not have been applicable to all people (flag = 1), but only to a specific region (flag = 0) (Hale et al. 2022a). The flag for E1 indicates "whether income support is for just formal sector workers (flag = 0) or whether it includes informal workers as well (flag = 1)" (ibid.). Additionally, a flag for H1 provides information on the payer of the vaccination, i.e., the individual (flag = 0) or the government (flag = 1) (ibid.).

Following the index calculation of Hale et al. (2021), subindex scores are calculated in a first step (Equation 1). For variables with flags, 0.5 is subtracted from the ordinal value of the respective variable "if the policy is targeted rather than general" (Hale et al. 2021: 536). The result is then divided by the maximum value of the variable and multiplied by 100. A missing value or a value of 0 yields a subindex score of 0 (Hale et al. 2022b).

(1) $$subindex\_score_{v,t} = 100 * \frac{value_{v,t} - 0.5 * \left(F_v - flag_{v,t}\right)}{N_v}$$

where v = any variable, t = any time, $value_{v,t}$ = government response as recorded, F_v = flag indicator (equal to 1 if the variable has a flag and equal to 0 if the variable does not have a flag), $flag_{v,t}$ = recorded flag, and N_v = maximum value of the variable (Hale et al. 2022b).

Like the subindex scores, the final indices are not weighted but are calculated using a simple average of the individual component indicators (Equations 2 through 4; Hale et al. 2021: 536).

(2) $$conclos\_index = \frac{1}{7} * (sub_{c1} + sub_{c3} + sub_{c4} + sub_{c5} + sub_{c6} + sub_{c7} + sub_{c8})$$

(3) $$econ\_index = \frac{1}{3} * (sub_{c2} + sub_{e1} + sub_{e2})$$

(4) $$health\_index = \frac{1}{6} * (sub_{h1} + sub_{h2} + sub_{h3} + sub_{h6} + sub_{h7} + sub_{h8})$$

Table 6 – Codebook of the OxCGRT dataset

ID	Name	Description	Coding		Flag
CCI	**Containment and Closure Index**				
C1	**School closing**	Record closings of schools and universities	0 1 2 3 Blank	No measures Recommend closing or all schools open with alterations resulting in significant differences compared to non-Covid-19 operations Require closing (only some levels or categories, e.g. just high schools, or just public schools) Require closing all levels No data	Geographic scope 0 - Targeted 1 - General Blank - No data
C3	**Cancel public events**	Record cancelling public events	0 1 2 Blank	No measures Recommend cancelling Require cancelling No data	Geographic scope 0 - Targeted 1 - General Blank - No data
C4	**Restrictions on gathering size**	Record limits on gatherings	0 1 2 3 4 Blank	No restrictions Restrictions on very large gatherings (the limit is above 1000 people) Restrictions on gatherings between 101-1000 people Restrictions on gatherings between 11-100 people Restrictions on gatherings of 10 people or less No data	Geographic scope 0 - Targeted 1 - General Blank - No data
C5	**Close public transport**	Record closing of public transport	0 1 2 Blank	No measures Recommend closing (or significantly reduce volume/route/means of transport available) Require closing (or prohibit most citizens from using it) No data	Geographic scope 0 - Targeted 1 - General Blank - No data
C6	**Stay-at-home requirements**	Record orders to "shelter-in-place" and otherwise confine to the home	0 1 2 3 Blank	No measures Recommend not leaving house Require not leaving house with exceptions for daily exercise, grocery shopping, and 'essential' trips Require not leaving house with minimal exceptions (e.g. allowed to leave once a week, or only one person can leave at a time, etc.) No data	Geographic scope 0 - Targeted 1 - General Blank - No data
C7	**Restrictions on internal movement**	Record restrictions on internal movement between cities/regions	0 1 2 Blank	No measures Recommend not to travel between regions/cities Internal movement restrictions in place No data	Geographic scope 0 - Targeted 1 - General Blank - No data

ID	Name	Description	Coding		Flag
C8	**Restrictions on international travel**	Record restrictions on international travel (for foreign travellers)	0 1 2 3 4 Blank	No restrictions Screening arrivals Quarantine arrivals from some or all regions Ban arrivals from some regions Ban on all regions or total border closure No data	
ERI	**Economic Response Index**				
E1	**Income support**	Record if the government is providing direct cash payments to people who lose their jobs or cannot work [Note: only includes payments to firms if explicitly linked to payroll/salaries]	0 1 2 Blank	No income support Government is replacing less than 50% of lost salary (or if a flat sum, it is less than 50% median salary) Government is replacing 50% or more of lost salary (or if a flat sum, it is greater than 50% median salary) No data	Sectoral scope 0 - Formal sector workers only or informal sector workers only 1 - All workers Blank - No data
E2	**Debt/contract relief for households**	Record if the government is freezing financial obligations for households (e.g. stopping loan repayments, preventing services like water from stopping, or banning evictions)	0 1 2 Blank	No debt/contract relief Narrow relief, specific to one kind of contract Broad debt/contract relief No data	
C2	**Workplace closing**	Record closings of workplaces	0 1 2 3 Blank	No measures Recommend closing (or recommend work from home) or all businesses open with alterations resulting in significant differences compared to non-Covid-19 operation Require closing (or work from home) for some sectors or categories of workers Require closing (or work from home) for all-but-essential workplaces (e.g. grocery stores, doctors) No data	Geographic scope 0 - Targeted 1 - General Blank - No data

ID	Name	Description	Coding		Flag
HSI	**Health System Index**				
H1	**Public information campaign**	Record presence of public info campaigns	0 1 2 Blank	No Covid-19 public information campaign Public officials urging caution about Covid-19 Coordinated public information campaign (e.g. across traditional and social media) No data	Geographic scope 0 - Targeted 1 - General Blank - No data
H2	**Testing policy**	Record government policy on who has access to testing [Note: this records policies about testing for current infection (PCR tests) not testing for immunity (antibody test)]	0 1 2 3 Blank	No testing policy Only those who both (a) have symptoms AND (b) meet specific criteria (e.g. key workers, admitted to hospital, came into contact with a known case, returned from overseas) Testing of anyone showing Covid-19 symptoms Open public testing (eg "drive through" testing available to asymptomatic people) No data	
H3	**Contact tracing**	Record government policy on contact tracing after a positive diagnosis	0 1 2 Blank	No contact tracing Limited contact tracing; not done for all cases Comprehensive contact tracing; done for all identified cases No data	
H6	**Facial coverings**	Record policies on the use of facial coverings outside the home	0 1 2 3 4 Blank	No policy Recommended Required in some specified shared/public spaces outside the home with other people present, or some situations when social distancing not possible Required in all shared/public spaces outside the home with other people present or all situations when social distancing not possible Required outside the home at all times regardless of location or presence of other people No data	Geographic scope 0 - Targeted 1 - General Blank - No data
H7	**Vaccination policy**	Record policies for vaccine delivery for different groups	0 1 2 3 4 5 Blank	No availability Availability for ONE of following: key workers/ clinically vulnerable groups (non elderly) / elderly groups Availability for TWO of following: key workers/ clinically vulnerable groups (non elderly) / elderly groups Availability for ALL of following: key workers/ clinically vulnerable groups (non elderly) / elderly groups Availability for all three plus partial additional availability (select broad groups/ages) Universal availability No data	Cost 0 - At cost to individual (or funded by NGO, insurance, or partially government funded) 1 - No or minimal cost to individual (government funded or subsidised) Blank - no data

ID	Name	Description	Coding		Flag
H8	**Protection of elderly people**	Record policies for protecting elderly people (as defined locally) in Long Term Care Facilities and/or the community and home setting	0	No measures	Geographic scope 0 - Targeted 1 - General Blank - No data
			1	Recommended isolation, hygiene, and visitor restriction measures in LTCFs and/or elderly people to stay at home	
			2	Narrow restrictions for isolation, hygiene in LTCFs, some limitations on external visitors and/or restrictions protecting elderly people at home	
			3	Extensive restrictions for isolation and hygiene in LTCFs, all non-essential external visitors prohibited, and/or all elderly people required to stay at home and not leave the home with minimal exceptions, and receive no external visitors	
			Blank	No data	

(Adapted from Hale et al. 2022a)

Erklärung über die Urheberschaft

Ich versichere hiermit an Eides statt, dass ich die vorliegende Abschlussarbeit selbstständig verfasst, ganz oder in Teilen noch nicht als Prüfungsleistung vorgelegt und keine anderen als die angegebenen Hilfsmittel benutzt habe. Sämtliche Stellen der Arbeit, die benutzten Werken im Wortlaut oder dem Sinn nach entnommen sind, habe ich durch Quellenangaben kenntlich gemacht. Dies gilt auch für Zeichnungen, Skizzen, bildliche Darstellungen und dergleichen sowie für Quellen aus dem Internet. Mir ist bewusst, dass es sich bei Plagiarismus um akademisches Fehlverhalten handelt, das sanktioniert werden kann.

Marburg, 28. Februar 2023

Simone Bresser