

Clustering and COVID-Era Immigration Policies

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Abstract

This paper explores the clusterings of countries and territories, by their immigration policies in the wake of COVID-19. We use K-means and Hierarchical Agglomerative Clustering (HAC) to create the clusters, with the gap statistic and cophenetic correlation to tune the hyperparameters required for each. We analyze the results of the clustering by attempting to find critical features of the “average” policy of each cluster. In addition, we use demographic variables, such as GDP, to understand trends among countries of similar immigration policies. We see very different results for between K-means and HAC. Moreover, we generally do not see clear patterns across these clusters, though there are some interesting findings at the smaller scale.

1 Introduction

With the onset of COVID-19, countries and territories scrambled to add an extra layer of protection with border closures and travel bans. Travel restrictions began as early as January 2020, such as North Korea’s complete border closure to foreign tourists, Hong Kong’s ban of residents or non-Hong Kong visitors from Chinese province Hubei, and Mozambique’s suspension of its visa upon arrival program for Chinese travelers [2, 8, 1]. Even from the beginning, countries and territories enforced COVID-19 immigration and travel policies that ranged the gamut. In the midst of so much variation, it is difficult to quantify how similar policies were to each other. Furthermore, strictness of policies were only relative, and we do not have a specific, clear spectrum on which to place each country. This paper attempts to make sense of that chaos, using two clustering methods to group countries by their COVID-19 immigration policies. How robust are the clusters to different clustering methods? What makes countries’ immigration policies similar, and how do they compare to natural groupings of countries? Finally, can we find demographic similarities between countries with similar policies?

2 Methods

2.1 Clustering Methods

The first type of clustering method we use is K-means, a non-deterministic algorithm for grouping the data into K clusters. We used the Hartigan-Wong method, which does not always merge the closest clusters, Hartigan-Wong is less prone to converge to a local optima [9]. It repeats until clusters converge, or the assignments of data points to different clusters do not change between iterations. The algorithm merges clusters that minimizes the sum of squared errors:

$$SSE = \sum_k^K \sum_{x_i \in c_k} (x_i - \mu_k)^2, \quad (1)$$

where μ_k is the cluster center for cluster c_k .

Data: Data set, $D = \{x_1, x_2, \dots, x_N\}$, and desired number of clusters, K

Result: Converged assignment for each data point, stored in list A

$A \leftarrow$ random initialization with K clusters;

$A_{prev} \leftarrow A$;

while $A \neq A_{prev}$ **do**

forall $x_i \in D$ **do**

$current_min \leftarrow$ SSE for current assignment $A[i]$;

forall k in $K, k \neq A[i]$ **do**

$potential_min \leftarrow$ SSE for potential assignment x_i to c_k ;

if $potential_min < current_min$ **then**

$current_min \leftarrow potential_min$;

$A[i] \leftarrow k$;

end

end

end

end

Algorithm 1: Hartigan-Wong Algorithm

Because K-means relies on a random initialization of cluster centers, we use 10 random restarts. The outcome of K-means would yield something like the figure below. We note that K-means works best with spherical data.

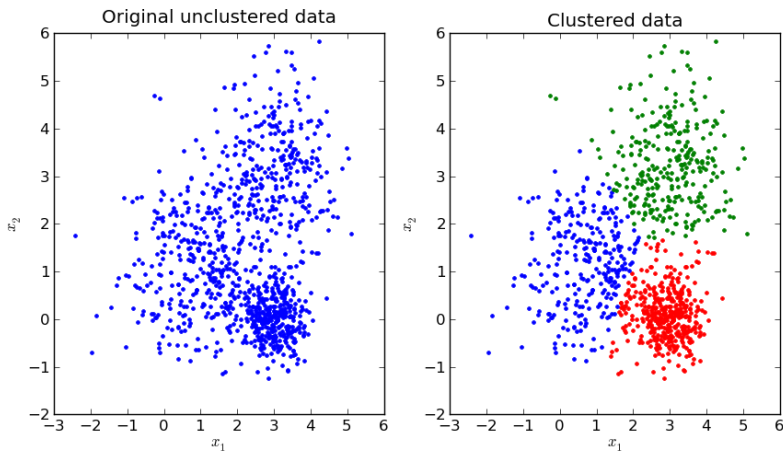


Figure 1: An example of the result of K-means, with $K = 3$ [7].

The other type of clustering method in this investigation is deterministic, Hierarchical Agglomerative Clustering (HAC). We iterate until all of the clusters have been merged together. We let $d(c_i, c_j)$ be the distance between the clusters i and j according to a linkage and metric criteria, which are discussed below.

Data: Data set, $D = \{x_1, x_2, \dots, x_N\}$, and desired number of clusters, K

Result: Assignment for each data point, stored in list A

$A \leftarrow A[i] = i, \forall i \in N;$

$A_{\text{prev}} \leftarrow A;$

/ To store heights of dendrogram, distance at which each cluster is merged. */*

$\text{heights} \leftarrow \{ \};$

while $\min(A) \neq \max(A)$ **do**

forall $i \in [\min(A), \max(A)]$ **do**

$\text{min_dist} \leftarrow \infty;$

$\text{closest_cluster} \leftarrow \text{None};$

forall $j \in [\min(A), \max(A)] \mid i \neq j$ **do**

$\text{potential_dist} \leftarrow d(c_i, c_j);$

if $\text{potential_dist} < \text{min_dist}$ **then**

$\text{min_dist} \leftarrow \text{potential_dist};$

$\text{closest_cluster} \leftarrow (i, j)$

end

end

end

/ Merge the two closest clusters and record the height. Closest_cluster is a tuple with the two indices of the closest clusters */*

$A \leftarrow$ Change the indices of the two closest clusters to $\min(\text{closest_cluster});$

$\text{heights} \leftarrow$ Add entry with $\text{min_dist}, \text{closest_cluster};$

end

Algorithm 2: Hierarchical Agglomerative Clustering (HAC)

Once the algorithm is finished, we construct a dendrogram. To obtain K clusters, we cut the dendrogram such that a horizontal line intersects K branches of the tree – an example can be seen in the following figure.

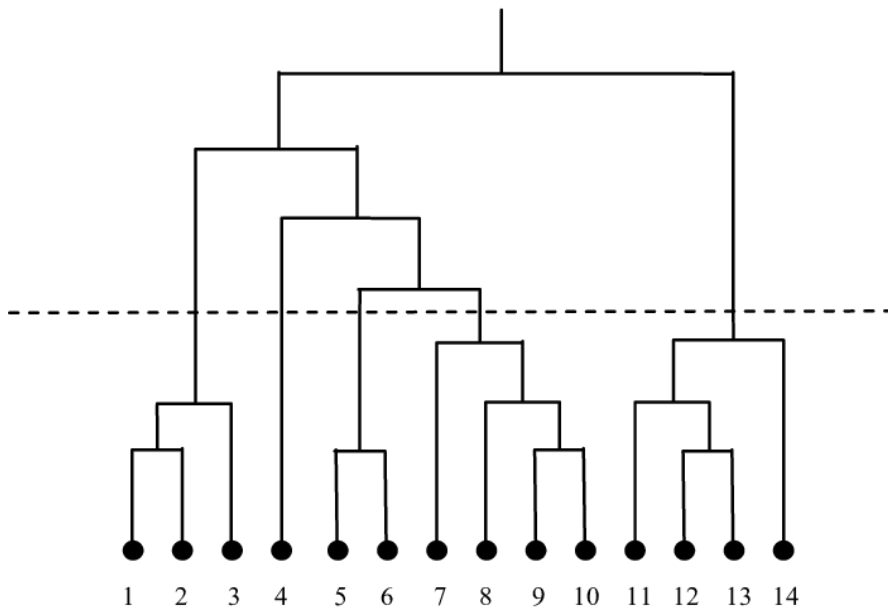


Figure 2: An example of a dendrogram after HAC, with a cut that will result in $K = 5$ clusters [3].

The metric and linkage criteria determine how and why clusters are merged together. The metric criteria is how the distance is measured; the most standard is Euclidian distance – the squared difference between

two points – which is what we use in our investigation.

The linkage criteria defines the closeness of clusters, or what the distance is calculated between. Unlike the metric criteria, there is not a “standard” linkage criteria, so we use cophenetic correlation to determine the most appropriate one [6]. This correlation quantifies how faithfully a dendrogram preserves the pair-wise distance between the original data points, with the minimum distance that merges two clusters at each iteration, or height of the tree when merging two clusters. Using $d(x_i, x_j)$ as the Euclidian distance between two points x_i, x_j , and $t(x_i, x_j)$ as the dendrogrammatic distance between the clusters of those same points, our cophenetic correlation, c , is:

$$c = \frac{\sum_{i < j} [d(x_i, x_j) - \bar{d}][t(x_i, x_j) - \bar{t}]}{\sqrt{\sum_{i < j} [x(i, j) - \bar{x}]^2 \sum_{i < j} [t(i, j) - \bar{t}]^2}} \quad (2)$$

For both K-Means and HAC, we also determine the number of clusters K that is best for the data. We use the gap statistic, which measures how different the total intra-cluster variation can be between observed data and reference data [10]. First, the data is grouped into K clusters, and the intra-cluster variation, W_K , is computed. Using n_k as the number of observations in cluster c_k , and $d(x_i, x_j)$ as the Euclidian distance between two points in a cluster:

$$W_K = \sum_{k=1}^K \frac{1}{2n_k} \sum_{x_i, x_j \in C_k} d(x_i, x_j), \quad (3)$$

The gap statistic is the deviation of W_K from its expected value, and is a measure of how much information we gain from clustering our data.

$$\text{Gap}(K) = \frac{1}{N} \sum_{r=1}^R [\log(W_{K,r}) - \log(W_K)] \quad (4)$$

Data: Data set, $D = \{x_1, x_2, \dots, x_N\}$ with M predictors, number of reference distributions, R ;
number of clusters K

Result: Gap statistic, G

$W_K \leftarrow$ equation 3;

/ We generate reference null distributions from the uniform distribution. This requires the minimum and maximum of each predictor. */*

/ The uniform distribution weights each point between the minimum and maximum can be chosen with equal probability, which is important for the null distribution. */*

forall $Y_i \in Y_M$ **do**

$a_{Y_i} \leftarrow \min(Y_i)$;

$b_{Y_i} \leftarrow \max(Y_i)$;

end

forall $r \in [1, R]$ **do**

forall $n \in N$ **do**

/ One draw from the uniform distributions: */*

$\text{ref}_n \leftarrow [\text{Unif}(a_{Y_1}, b_{Y_1}), \dots, \text{Unif}(a_{Y_M}, b_{Y_M})]$;

end

$W_{(K, r)} \leftarrow [\text{ref}_1, \text{ref}_2, \dots, \text{ref}_{(n-1)}, \text{ref}_n]$;

end

$\text{gap}_K \leftarrow$ equation 4

Algorithm 3: Gap Statistic

Intuitively, we want to maximize this statistic, but we need to set an upper bound to limit computational expense, and to avoid simply classifying each data point in its own cluster. Thus, to strike a balance, we choose the smallest k value such that $\text{Gap}(k) \geq \text{Gap}(k+1) - \sigma(k+1)$ [10].

2.2 Data

Our data on immigration policies is from the COVID Border Accountability Project. The original data set has 44 variables that describe different aspects of the immigration policies, which we narrow down to fifteen instead. The chosen variables answer the questions of whom the policies affected, how long they were put in place, and how they were enforced across different mediums of travel. It is reasonable to say that the answers paint a representative picture of an immigration policy. To check whether these variables are redundant, we compute the correlation matrix (see table 5), and find that the correlation between each pair of relevant variables all have absolute values less than 0.75¹, a reasonable threshold for what is considered a high correlation. Thus, we do not further narrow down our variables.

Below are summary statistics for each chosen variable. More specific data description and data cleaning choices are described in the [appendix](#).

¹All correlation values are less than 0.75, except for several variables from one-hot encoding, since the one-hot encoding extends over several columns. Being in one category inherently means that the observation was not in the other category, which yields a high correlation.

Variable Name	Min	Max	Mean	Standard Deviation
VISA_BAN_NONE	0	1	0.9642	0.18573097
VISA_BAN_SPECIFIC	0	1	0.01192	0.10854914
VISA_BAN_ALL	0	1	0.02384	0.15258303
HISTORY_BAN	0	236	7.09	34.05137459
CITIZEN_LIST	0	229	11.71	45.63653721
POLICY_LENGTH	14	827	118.6	178.28649617
POLICY_TYPE_COMPLETE	0	1	0.2395	0.42689984
POLICY_TYPE_PARTIAL	0	1	0.7565	0.42930020
POLICY_TYPE_NON	0	1	0.003973	0.06292235
AIR	0	1	0.391	0.48812027
LAND	0	1	0.1425	0.34961211
SEA	0	1	0.1294	0.33573566
REFUGEE	0	1	0.001703	0.04123927
COUNTRY_EXCEP	0	1	0.07775	0.26785782
WORK_EXCEP	0	1	0.07378	0.26148641

Table 1: Statistics for the quantitative selected variables. Each variable was standardized, but the original statistics are more meaningful to report.

We also use demographic data from the World Bank. We use fairly standard demographic variables: GDP, population, life expectancy, education rate, and fertility rate. Furthermore, we collect the countries’ development status (using the Human Development Index²) and continent, since this information naturally groups different countries together. They are useful for us to compare to our clustering of countries by immigration policy.

2.3 Analysis Methods

Our analysis consists of three main methods. The first is a multiple sample T-test on the chosen demographic factors, across the different clusters formed by K-means and HAC. Another result is a scatter plot of the countries, color-coded by their K-means and HAC clusters, on both demographic and policy-related axes. Because the policy-related variables are used to cluster the countries, we want to retain as much of that information as possible, while also visualizing them reasonably on a two-way axis. Thus, we use Principal Component Analysis (PCA) to find the top two principal components, which preserve the most variance of the data.

On the other hand, we do not use the demographic variables to cluster our countries, so the two-way plots are created more for interpretation and visualization, so we do not use PCA. Instead, we look at all $\binom{5}{2} = 10$ combinations (for each clustering method) of demographic variables as axes, and widely examine them for any clustering patterns.

Finally, to compare HAC and K-Means to the more intuitive clustering by continent and development, we use the rand index [5]. Suppose we have two clusterings, X and Y , of a data set S of size N . The rand index is defined as:

$$R = \frac{a + b}{\binom{N}{2}}, \quad (5)$$

where a is the number of pairs that are placed in the same cluster in both the X and Y schemes, and b is the number of pairs that are placed in different clusters in both schemes. Thus, a value R close to 1 is an indicator of similar clusterings.

3 Results

We find that 6 clusters (see figure 10) are chosen by the gap statistic. Furthermore, the average linkage, which defines the distance between two clusters as the average of distances between all possible pairs of different clusters’ data points, yielded the highest cophenetic correlation (see table 6).

We compute the rand index between the more “natural clustering of the countries on their continent and development level, and the clustering generated by K-means and HAC. We see that K-means and HAC themselves yielded somewhat dissimilar clusters, with a rand index of 0.594.

Policy Clustering	Continent	Development Level
K-Means	0.542	0.527
HAC	0.318	0.312

Table 2: The rand index for different clustering methods and their more natural counterparts.

²“HDI classifications are based on HDI fixed cutoff points, which are derived from the quartiles of distributions of the component indicators. The cutoff-points are HDI of less than 0.550 for low human development, 0.550–0.699 for medium human development, 0.700–0.799 for high human development and 0.800 or greater for very high human development.” [4]

For two and three demographic variables across HAC and K-means, respectively, we find a significant result on a two-sided hypothesis test. There is at least one cluster that differs significantly from the overall group mean in these variables.

Demographic	K-Means	HAC
GDP	0.0383	4.29×10^{-5}
Population	0.0751	0.922
Life Expectancy	0.0166	0.0215
Fertility Rate	0.192	0.415
Literacy Rate	0.248	0.482

Table 3: P-values of multiple-sample t-tests for demographic characteristics across different clusters. Significant p-values (< 0.05) are bolded.

For variables with a statistically significant difference from the group mean, we further investigate their distributions with boxplots. For all following boxplots, we are able to see fairly stark differences in each cluster’s mean. Furthermore, there are many outliers.

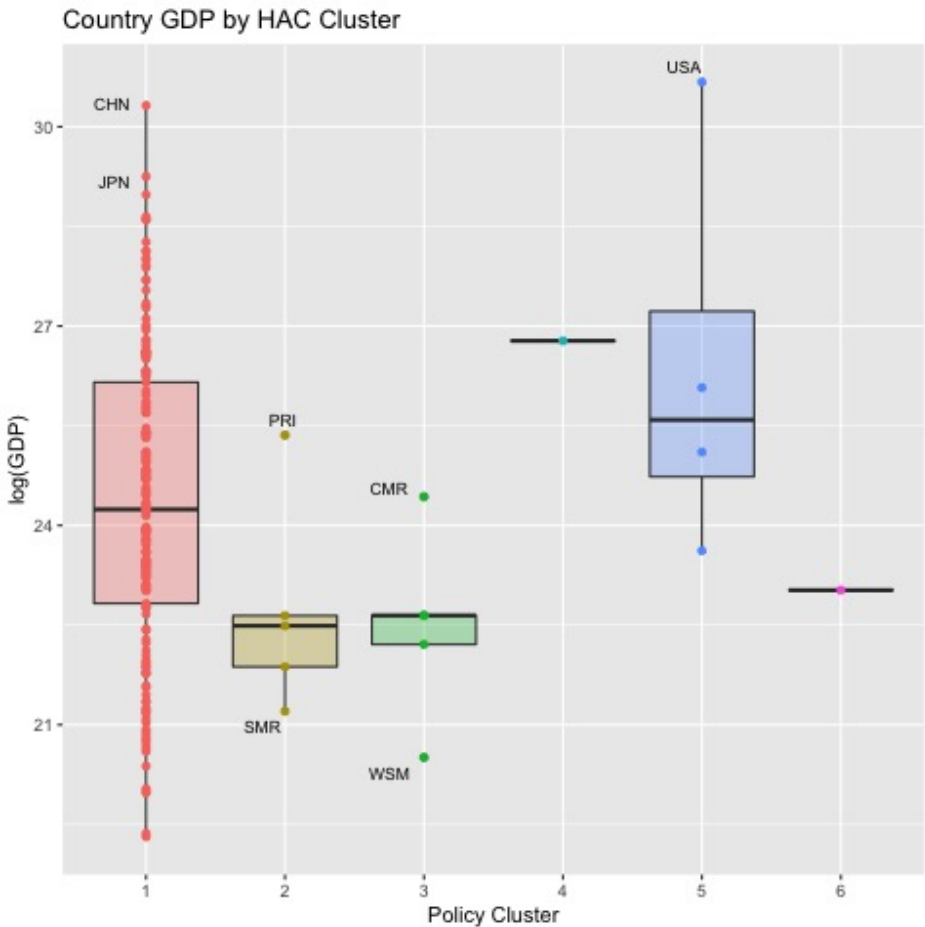


Figure 3: A boxplot of (log of) GDP for the countries in specific HAC clusters. Outliers for each group are labelled with their [ISO3 code](#). We take the log of the GDP because it is extremely right-skewed, given the extreme inequity of wealth distribution. (Not doing so would lead to many outliers on the upper end, which are difficult to distinguish and label.)

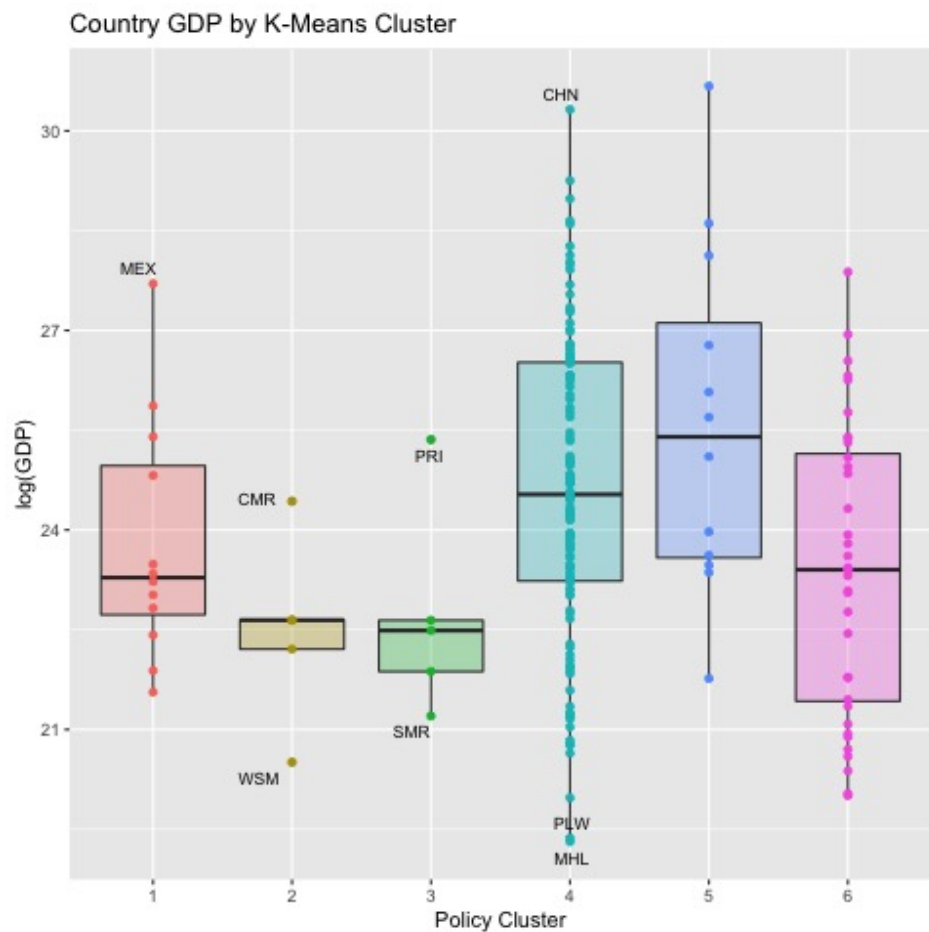


Figure 4: A boxplot of (log of) GDP for the countries in specific K-Means clusters. Outliers for each group are labelled with their [ISO3 code](#). We take the log of the GDP because it is extremely right-skewed, given the extreme inequity of wealth distribution. (Not doing so would lead to many outliers on the upper end, which are difficult to distinguish and label.)

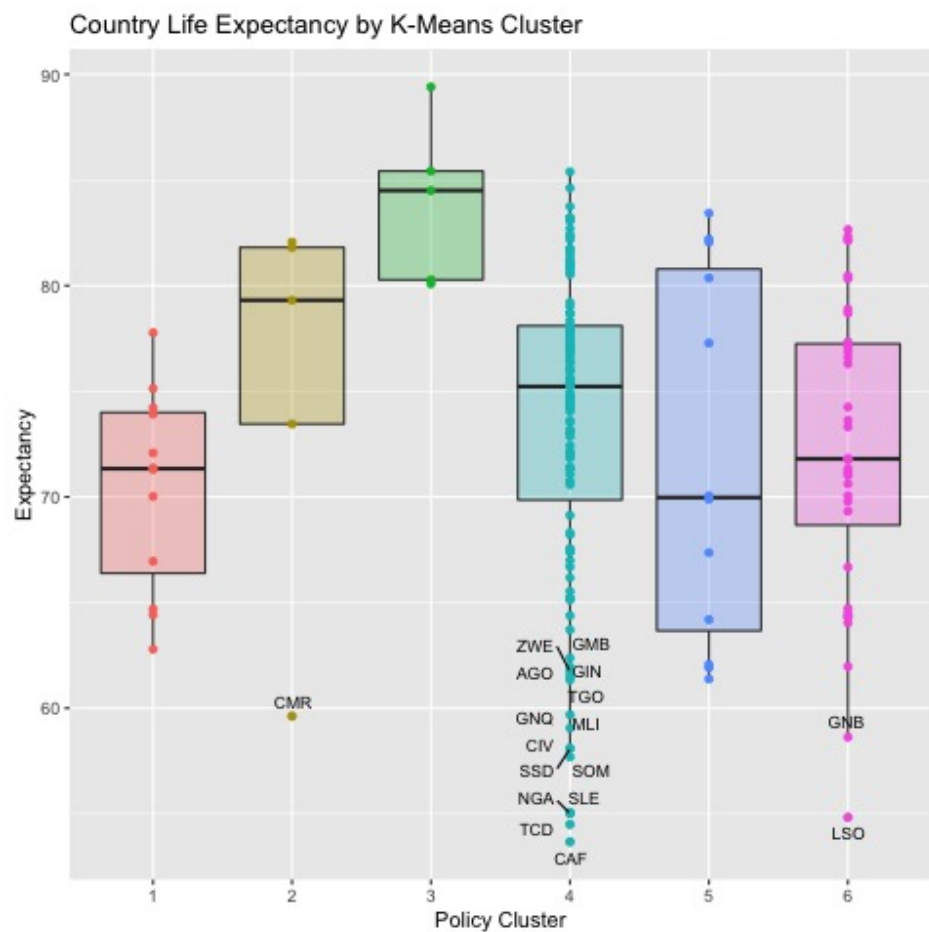


Figure 5: A boxplot of life expectancy for the countries in specific K-means clusters. Outliers for each group are labelled with their [ISO3 code](#).

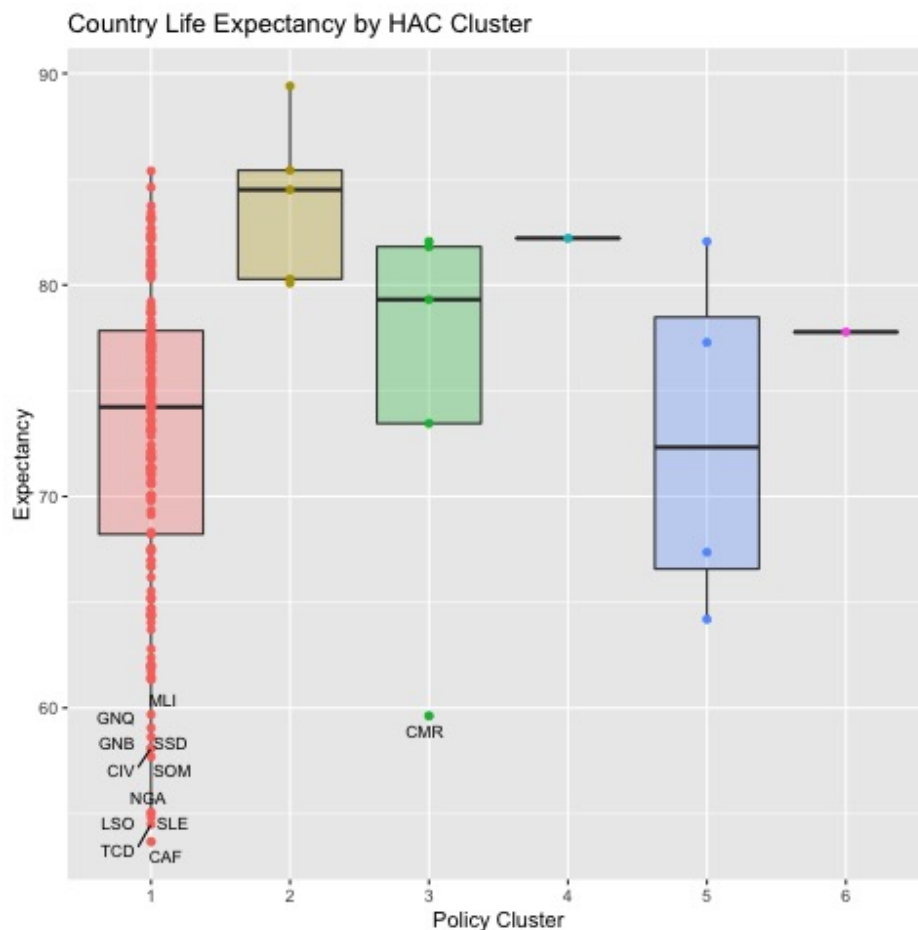


Figure 6: A boxplot of life expectancy for the countries in specific HAC clusters. Outliers for each group are labelled with their [ISO3 code](#).

In addition, we include a boxplot of a variable that was not associated with a significant test result, specifically literacy across the different HAC clusters. Although we see many outliers in cluster 1, we do note that the group means seem to be visually close to each other.

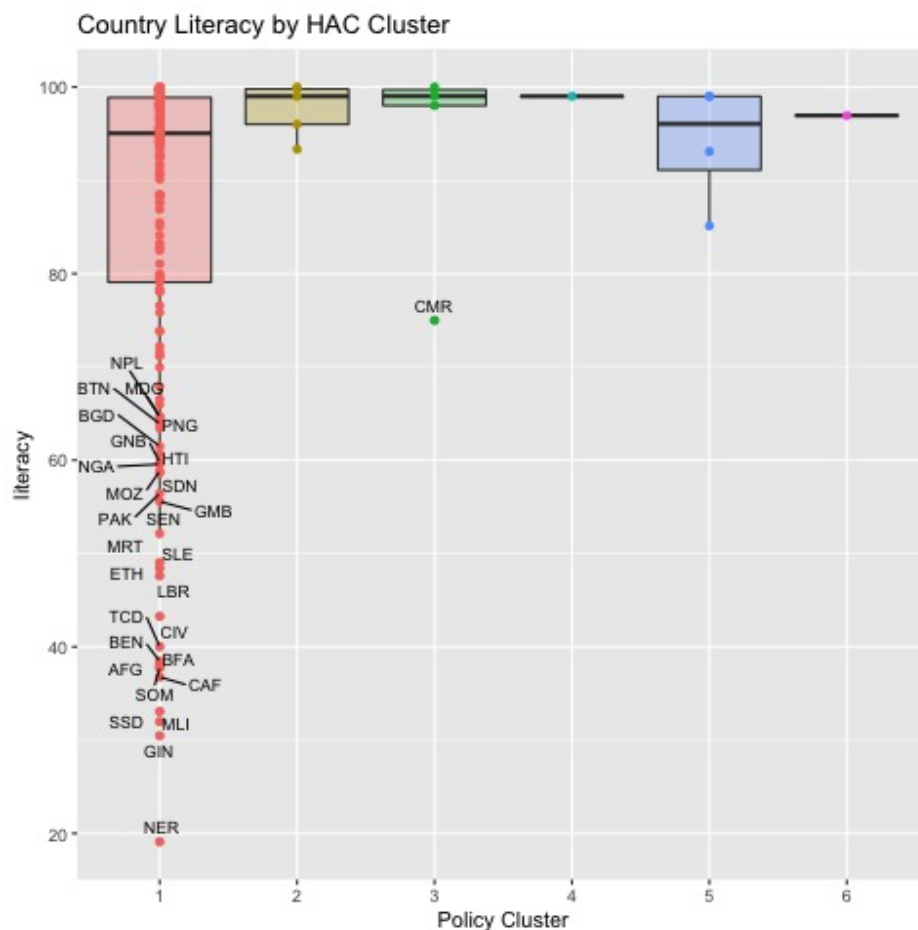


Figure 7: A boxplot of literacy rates for the countries in specific HAC clusters. Outliers for each group are labelled with their [ISO3 code](#).

Finally, we report several two-way plots, on both policy-related and demographic variables.



Figure 8: A plot of countries versus their two principal components, for both HAC and K-means clustering.

Including all combinations in this report is not necessarily meaningful, so we report two plots that are generally representative of the scattering of the clusters throughout.

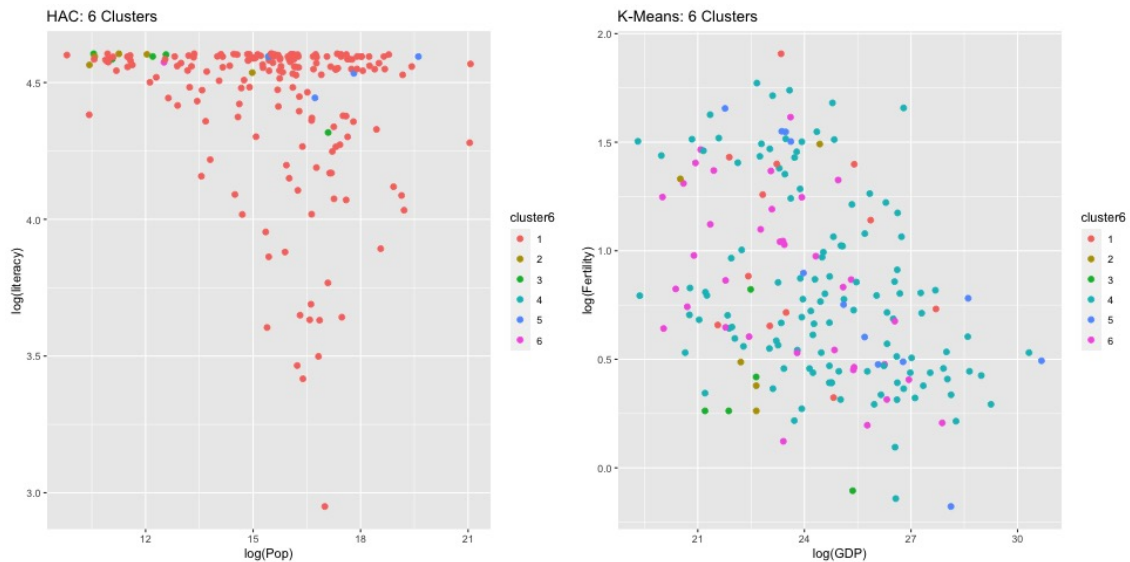


Figure 9: Two-way plots of countries on certain demographic factors, to demonstrate the point that we cannot find a clear trend. A graph is chosen for each clustering method. We take the log of each demographic variables for ease of visibility.

4 Discussion

4.1 Statistical Discussion

First, by table 2, we see that K-means clusters are more similar to the natural clusterings of continents and development levels. In particular, HAC produces very uneven clusters: the first cluster is very large, followed by some sparse ones. Although K-means also produces one large cluster, the remaining data points are spread out through the others. In contrast, from general knowledge of continents and development stratifications, we know that there is no single group that contains an unduly high number of countries. Thus, we expect that the rand index would be quite low for HAC versus these natural clusterings. To be specific, the a in equation 5 would be quite high for the HAC clustering, because a lot of the pairs are in the same, very large cluster. It is quite unlikely that we would see this phenomena be replicated with a more even clustering.

HAC produces such disparately sized clusters because of the data's structure. The PCA plots in figure 8 show that the majority of the data points are already fairly close to each other. The average linkage considers the Euclidian distance of all possible pairwise combinations of points in those clusters. If the majority of those points already begin close to each other, they will have the greatest influence on an overall small average distance between intermediate clusters, which eventually merge into the final large cluster. Although clusters formed by the average linkage criteria are not as prone to this "chaining of clusters as its single linkage counterparts, we see that the inherent structure of the data can cause this phenomena instead.

Furthermore, as in table 3, we see that the p-values for the K-means are notably, on average, must smaller than that of HAC. Furthermore, we see that K-means have three significant p-values, whereas HAC has two. We attribute the decreased power of the significance test on the HAC clusters to the much more unevenly-sized HAC clusters, as explained above. Uneven sample sizes exacerbate any unequal variance issues, which increases the Type I error of the test.

4.2 Social Science Discussion

There are several interesting social patterns. We use tables 11 and 12 to identify countries or territories in each cluster, 10 and 9 for their demographic characteristics, and 7 and 8 for their policy characteristics.

By K-means clustering, we find that cluster 5 (Burundi, Benin, India, Ireland, Cambodia, North Korea, South Korea, Burma, Myanmar, Mozambique, New Zealand, Qatar, United States, Zambia) has particularly severe visa bans and longer than average policy lengths, while cluster 2 (Bermuda, Barbados, Cameroon, Liechtenstein, Samoa) made exceptions to their immigration and travel restrictions for more countries.

For HAC clusters, to name a few: cluster 2 (Andorra, Guam, Monaco, Puerto Rico, San Marino) is mainly defined by entities that did not fully enforce their immigration policies, and cluster 5 (Burma, Myanmar, New Zealand, United States, Zambia) were known for policies that targeted refugees and asylum seekers. We see that, with these two clustering methods, immigration policies cannot necessarily be similar to each other simply by a black-and-white metric of strictness. If this were the case, we would see clusters with consistently low or high values for each policy variable. There are many nuances to how a policy can be enforced, and this result is especially emphasized in the clusterings we produce.

Furthermore, we see that the countries in their respective policy clusters differ on at least a few demographic measures from table 3 and our boxplots. For example, cluster 2 by K-means (Bermuda, Barbados, Cameroon, Liechtenstein, Samoa) with the country exceptions, and cluster 2 by HAC (Andorra, Guam, Monaco, Puerto Rico, San Marino) with more relaxed enforcement have a lower GDP than most other clusters. Although more research would need to be done, perhaps they do not have natural resources to generate such a high GDP, and instead rely on tourism, and thus open borders, for a large portion of their GDP. Furthermore, we can speculate on why Burma, Myanmar, New Zealand, United States, Zambia (cluster 5 for HAC) targeted refugees in particular; perhaps they are carrying out similar immigration policies even before COVID-19, with a history of welcoming or turning away refugees.

However, these demographic differences are not enough to establish a clear trend of stricter countries having certain demographic qualities, which mostly speaks to the aforementioned unclear definition of “strictness” across clusters in the first place. When we look at the boxplots with significant test results, we do not see one cluster with both the highest GDP and life expectancy (two indicators of wealth) across both types of clustering. We cannot say that, across the board, countries of a certain development level enforced similar policies. A lack of clear distinction of clusters in the representative figure 9 further reinforces that point.

5 Conclusion and Future Directions

Overall, we are not able to find clear patterns, at least with these two methods of clustering. However, this investigation is still valuable in that it simply speaks to the noise of the data and the global situation at large. Of course, this clustering investigation can be expanded in many ways. We can select different combinations of variables from the current data-set, clean the data set to account for different levels of reliability, and even expand on the current data with web scraping of our own. Furthermore, there are plenty of other clustering methods that could possibly uncover patterns, especially ones that are less susceptible to “chaining.” Finally, there exist other analysis methods, especially ones that are social science-specific, that can be used to uncover more patterns than our examination of boxplots and group means.

6 Appendix

More on data cleaning: The original data set also required some cleaning. Initially, each observation denoted a policy, and the data set had many missing values. Because the purpose of the investigation is to examine clusters of different countries’ policies, we aggregate the data set by country. Data cleaning ensures that each variable (besides the identifiers, country name and ISO3) is quantitative, even if that is a 0 or 1; this allows us to average our observations while collapsing them. As for the high proportion of NA values, we determine that the data is not missing at-random, and rather, an NA value often denotes the absence of a variable. For example, an NA value for the variable that lists any history of travel bans simply indicates that the country did not bar entry for any people who had traveled to specific countries. The specific data cleaning choices, as well as variable descriptions, are summarized below:

Variable Name	Description	Data Cleaning (if applicable)
COUNTRY_NAME	The name of each country	N/A
ISO3	The standardized three-letter country codes defined in ISO 3166-1	N/A
VISA_BAN_NONE	A binary indicator of whether no visa seekers were targeted (1) or not (0)	One-hot encoding
VISA_BAN_SPECIFIC	A binary indicator of whether specific visa seekers were targeted (1) or not (0)	One-hot encoding
VISA_BAN_ALL	A binary indicator of whether all visa seekers were targeted (1) or not (0)	One-hot encoding
HISTORY_BAN	The number of countries from which travelers were banned	Counting the number of countries listed and replacing NA values with zeroes
CITIZEN_LIST	The number of countries for which its citizens were banned	Counting the number of countries listed and replacing NA values with zeroes
POLICY_LENGTH	The number of days that the policy was enforced	Calculating the time elapsed between the start and end dates
POLICY_TYPE_COMPLETE	A binary value indicator of whether the policy was completely implemented (1) or not (0)	One-hot encoding
POLICY_TYPE_PARTIAL	A binary value indicator of whether the policy was partially implemented (1) or not (0)	One-hot encoding
POLICY_TYPE_NON	A binary value indicator of whether the policy was implemented to any degree (0) or not (1)	One-hot encoding
AIR	A binary value indicator of whether there was border air closure (1) or not (0)	N/A
LAND	A binary value indicator of whether there was air border closure (1) or not (0)	N/A
SEA	A binary value indicator of whether there was sea border closure (1) or not (0)	N/A
REFUGEE	A binary value indicator of whether the policy language used the phrases “refugee or “asylum seeker (1) or not (0)	N/A
COUNTRY_EXCEP	A binary value indicator of whether any countries were exempted from complete closure (1) or not (0)	N/A
WORK_EXCEP	A binary value indicator of whether the policy exempted any workers (1) or not (0)	N/A

Table 4: A table describing each chosen variable of the data, as well as any data cleaning that was used in the investigation.

	VBN	VBS	VBA	HBC	CLC	PL	PTC	PTP	AIR	LAND	SEA	PTN	REF	CE	WE
VISA_BAN_NONE	1														
VISA_BAN_SPECIFIC	-0.57	1													
VISA_BAN_ALL	-0.81	-0.02	1												
HISTORY_BAN_CLEANED	0.04	-0.02	-0.03	1											
CITIZEN_LIST_CLEANED	0.05	-0.03	-0.04	-0.05	1										
POLICY_LENGTH	-0.17	0.09	0.14	-0.09	-0.09	1									
POLICY_TYPE_COMPLETE	0.11	-0.06	-0.09	-0.12	-0.14	0.07	1								
POLICY_TYPE_PARTIAL	-0.11	0.06	0.09	0.12	0.15	-0.06	-0.99	1							
AIR	0.15	-0.09	-0.13	-0.17	-0.21	-0.14	-0.45	0.45	1						
LAND	0.08	-0.04	-0.06	-0.08	-0.1	0.07	-0.23	0.23	0.07	1					
SEA	0.07	-0.04	-0.06	-0.08	-0.1	-0.07	-0.22	0.22	0.42	0.29	1				
POLICY_TYPE_NON	0.01	-0.01	-0.01	-0.01	-0.02	-0.04	-0.04	-0.11	-0.05	-0.03	-0.02	1			
REFUGEE	0.01	0	-0.01	-0.01	-0.01	0.05	-0.02	0.02	-0.03	-0.02	-0.02	0	1		
COUNTRY_EXCEP	0.06	-0.03	-0.05	-0.06	-0.07	-0.02	0.52	-0.51	-0.23	-0.12	-0.11	-0.02	-0.01	1	
WORK_EXCEP	0.05	-0.03	-0.04	-0.06	-0.07	0.01	0.5	-0.5	-0.23	-0.12	-0.11	-0.02	-0.01	0.39	1

Table 5: The correlation matrix for all of the policy-related variables. The columns are abbreviated for sake of space, but they follow the same order as the rows, for reference.

According to the figures below, we would naively pick one cluster for K-means. However, this result is not particularly meaningful anyways, and we see that one cluster is chosen because the gap statistic decreases immediately after. Furthermore, we make a design decision that the number of clusters chosen by HAC and K-means be more than within a factor of 2 of each other, for more interpretable results when it comes to t-tests, for example. Thus, we cautiously proceed and see that the number of clusters for K-means is also 6.

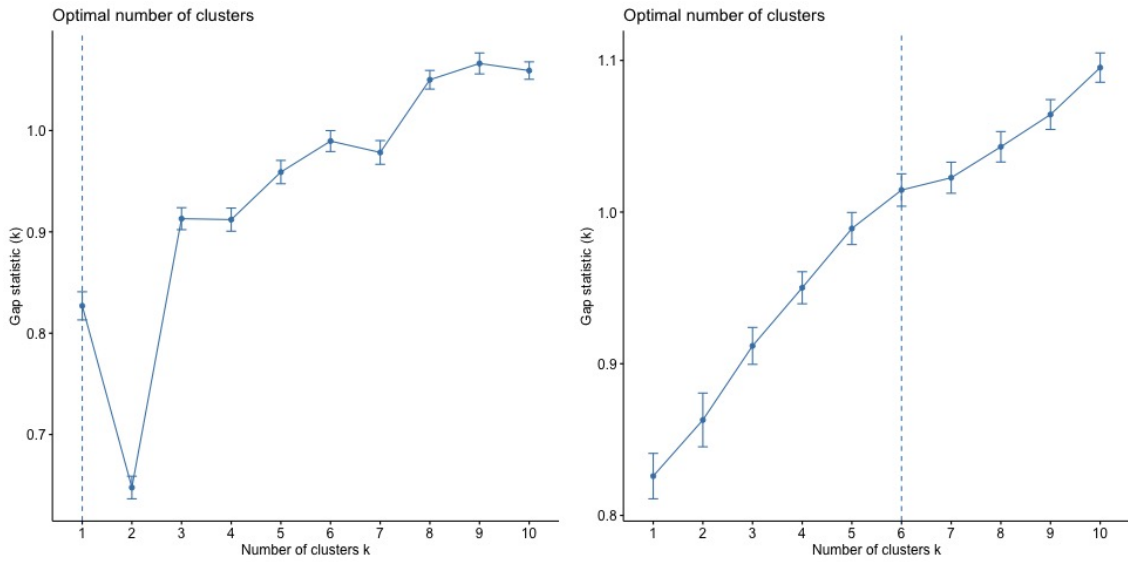


Figure 10: The gap statistic versus the number of clusters, for both clustering methods. An optimal six clusters was chosen, based on the cutoff described in the methods section.

Linkage Criteria	Description	Cophenetic Correlations
Average	Cluster closeness is defined as the average distance between all pairs in each cluster.	0.973
Complete	Cluster closeness is defined as the distance between the farthest points of the clusters.	0.884
Centroid	Cluster closeness is defined as the distance between the cluster centroids.	0.970
Single	Cluster closeness is defined as the distance between the closest points of the clusters.	0.951
Ward	Cluster closeness is defined as, if those two clusters are merged, they minimize the total within-cluster variance.	0.845
Mcquitty	Cluster closeness is defined recursively; the distance of the most recently merged clusters (let's call them <i>A</i> and <i>B</i>) from a cluster we now consider merging (let's call it <i>C</i>) is the average of the distances from <i>A</i> to <i>C</i> , and <i>B</i> to <i>C</i> .	0.948
Median	Cluster closeness is defined as the distance between the cluster medians.	0.942

Table 6: The cophenetic correlations for different linkage criteria.

cluster	VISA_BAN_NONE	VISA_BAN_SPECIFIC	VISA_BAN_ALL	HISTORY_BAN_CLEANED
1	0.10	0.04	-0.16	-0.20
2	0.19	-0.11	-0.16	-0.21
3	0.19	-0.11	-0.16	-0.21
4	0.09	-0.05	-0.07	-0.07
5	-1.95	0.86	1.77	-0.19
6	0.19	-0.11	-0.16	-0.18

cluster	CITIZEN_LIST_CLEANED	POLICY_LENGTH	POLICY_TYPE_NON	POLICY_TYPE_COMPLETE
1	-0.23	2.40	-0.06	-0.05
2	-0.26	-0.23	-0.06	1.78
3	-0.26	-0.66	15.83	-0.56
4	-0.07	0.03	-0.06	-0.22
5	-0.25	0.65	-0.06	-0.32
6	-0.22	0.04	-0.06	1.03

cluster	POLICY_TYPE_PARTIAL	AIR	LAND	SEA
1	0.06	-0.39	0.82	-0.27
2	-1.76	-0.80	-0.41	-0.39
3	-1.76	-0.80	-0.41	-0.39
4	0.22	0.08	0.10	-0.07
5	0.33	-0.30	0.17	-0.08
6	-1.01	-0.54	-0.21	-0.27

cluster	REFUGEE	COUNTRY_EXCEP
1	-0.04	0.16
2	-0.04	0.46
3	-0.04	-0.29
4	-0.01	-0.22
5	0.08	-0.19
6	-0.04	0.06

Table 7: The means of (standardized) policy-related variables for K-means clustering.

cluster	VISA_BAN_NONE	VISA_BAN_SPECIFIC	VISA_BAN_ALL	HISTORY_BAN_CLEANED
1	0.05	-0.03	-0.04	-0.11
2	0.19	-0.11	-0.16	-0.21
3	0.19	-0.11	-0.16	-0.21
4	-4.12	5.42	1.16	-0.21
5	-2.33	0.03	2.82	-0.18
6	0.19	-0.11	-0.16	-0.21

cluster	CITIZEN_LIST_CLEANED	POLICY_LENGTH	POLICY_TYPE_NON	POLICY_TYPE_COMPLETE
1	-0.12	0.20	-0.06	0.04
2	-0.26	-0.66	15.83	-0.56
3	-0.26	-0.23	-0.06	1.78
4	-0.26	0.20	-0.06	-0.56
5	-0.26	0.61	-0.06	-0.37
6	-0.26	3.65	-0.06	1.78

cluster	POLICY_TYPE_PARTIAL	AIR	LAND	SEA
1	-0.03	-0.09	0.10	-0.12
2	-1.76	-0.80	-0.41	-0.39
3	-1.76	-0.80	-0.41	-0.39
4	0.57	-0.39	-0.41	0.21
5	0.37	-0.37	-0.06	-0.39
6	-1.76	-0.80	-0.41	-0.39

cluster	REFUGEE	COUNTRY_EXCEP
1	-0.02	-0.16
2	-0.04	-0.29
3	-0.04	0.46
4	-0.04	-0.29
5	0.32	0.02
6	-0.04	3.44

Table 8: The means of (standardized) policy-related variables for HAC.

cluster	GDP	Pop	Expectancy	Fertility	literacy
1	3.538×10^{11}	4.034×10^7	72.86	2.58	85.78
2	2.411×10^{10}	7.027×10^7	83.94	1.46	97.62
3	1.194×10^{10}	5.427×10^6	75.25	2.52	94.34
4	4.259×10^{11}	4.994×10^6	82.20	1.63	99.00
5	5.315×10^{12}	1.018×10^8	72.72	2.47	94.05
6	1.000×10^{10}	2.720×10^5	77.77	1.92	96.94

Table 9: The means of demographic variables for HAC.

cluster	GDP	Pop	Expectancy	Fertility	literacy
1	1.237×10^{11}	2.795×10^7	70.390	3.121	76.973
2	1.194×10^{10}	5.427×10^6	75.249	2.523	94.340
3	2.411×10^{10}	7.026×10^5	83.937	1.459	97.624
4	4.345×10^{11}	3.987×10^7	73.499	2.496	86.604
5	2.182×10^{12}	1.599×10^8	71.851	2.787	83.690
6	9.801×10^{10}	1.089×10^7	72.309	2.571	88.277

Table 10: The means of demographic variables for K-means.

Cluster	Countries and Territories
1 ($n = 12$)	Belarus, Bhutan, Ethiopia, Georgia, Guyana, Kazakhstan, Liberia, Mexico, Malawi, New Caledonia, Niger, Tajikistan
2 ($n = 5$)	Bermuda, Barbados, Cameroon, Liechtenstein, Samoa
3 ($n = 5$)	Andorra, Guam, Monaco, Puerto Rico, San Marino
4 ($n = 125$)	Aruba, Afghanistan, Angola, Albania, United Arab Emirates, Argentina, Armenia, Antigua and Barbuda, Australia, Austria, Azerbaijan, Belgium, Bangladesh, Bulgaria, Bahrain, Bahamas, Bosnia and Herzegovina, Belize, Brazil, Brunei, Central African Republic, Canada, Switzerland, China, Ivory Coast, Colombia, Cape Verde, Cyprus, Germany, Djibouti, Denmark, Algeria, Egypt, Estonia, Fiji, France, Gabon, United Kingdom, Guinea, Gambia, Equatorial Guinea, Greece, Grenada, Greenland, Guatemala, Hong Kong, Honduras, Croatia, Hungary, Indonesia, Iraq, Iceland, Israel, Italy, Jamaica, Jordan, Japan, Kenya, Kuwait, Lebanon, Libya, Saint Lucia, Sri Lanka, Lithuania, Luxembourg, Latvia, Morocco, Madagascar, Maldives, Marshall Islands, Mali, Montenegro, Mauritania, Mauritius, Nigeria, Nicaragua, Netherlands, Norway, Nepal, Oman, Pakistan, Panama, Peru, Philippines, Palau, Poland, Portugal, Paraguay, French Polynesia, Romania, Russia, Saudi Arabia, Sudan, Senegal, Singapore, Solomon Islands, Sierra Leone, El Salvador, Somalia, Serbia, South Sudan, Sao Tome and Principe, Slovenia, Sweden, Seychelles, Turks and Caicos Islands, Chad, Togo, Turkmenistan, Tunisia, Turkey, Uganda, Uruguay, Uzbekistan, Venezuela, Viet Nam, Yemen, South Africa, Zimbabwe
5 ($n = 14$)	Burundi, Benin, India, Ireland, Cambodia, North Korea, South Korea, Burma, Myanmar, Mozambique, New Zealand, Qatar, United States, Zambia
6 ($n = 37$)	American Samoa, Burkina Faso, Bolivia, Botswana, Chile, Comoros, Costa Rica, Cuba, Cayman Islands, Dominica, Dominican Republic, Ecuador, Eritrea, Spain, Finland, Ghana, Gibraltar, Guinea-Bissau, Haiti, Kyrgyzstan, Saint Kitts and Nevis, Lesotho, Malta, Mongolia, Northern Mariana Islands, Malaysia, Namibia, Papua New Guinea, Rwanda, Suriname, Slovakia, Thailand, Tonga, Trinidad and Tobago, Ukraine, Vanuatu

Table 11: Countries and territories clustered together under K-Means.

Cluster	Countries and Territories
1 ($n = 181$)	Aruba, Afghanistan, Angola, Albania, United Arab Emirates, Argentina, Armenia, American Samoa, Antigua and Barbuda, Australia, Austria, Azerbaijan, Burundi, Belgium, Benin, Burkina Faso, Bangladesh, Bulgaria, Bahrain, Bahamas, Bosnia and Herzegovina, Belarus, Belize, Bolivia, Brazil, Brunei, Bhutan, Botswana, Central African Republic, Canada, Switzerland, Chile, China, Côte d'Ivoire, Colombia, Comoros, Cape Verde, Costa Rica, Cuba, Cayman Islands, Cyprus, Germany, Djibouti, Dominica, Denmark, Dominican Republic, Algeria, Ecuador, Egypt, Eritrea, Spain, Estonia, Ethiopia, Finland, Fiji, France, Gabon, United Kingdom, Georgia, Ghana, Gibraltar, Guinea, Gambia, Guinea-Bissau, Equatorial Guinea, Greece, Grenada, Greenland, Guatemala, Guyana, Hong Kong, Honduras, Croatia, Haiti, Hungary, Indonesia, India, Iraq, Iceland, Israel, Italy, Jamaica, Jordan, Japan, Kazakhstan, Kenya, Kyrgyzstan, Cambodia, North Korea, South Korea, Kuwait, Lebanon, Liberia, Libya, Saint Lucia, Sri Lanka, Lesotho, Lithuania, Luxembourg, Latvia, Morocco, Madagascar, Maldives, Mexico, Marshall Islands, Mali, Malta, Montenegro, Mongolia, Northern Mariana Islands, Mozambique, Mauritania, Mauritius, Malawi, Malaysia, Namibia, Niger, Nigeria, Nicaragua, Netherlands, Norway, Nepal, Oman, Pakistan, Panama, Peru, Philippines, Palau, Papua New Guinea, Poland, Portugal, Paraguay, French Polynesia, Qatar, Romania, Russia, Russian Federation, Rwanda, Saudi Arabia, Sudan, Senegal, Singapore, Solomon Islands, Sierra Leone, El Salvador, Somalia, Serbia, South Sudan, Sao Tome and Principe, Suriname, Slovakia, Slovenia, Sweden, Seychelles, Turks and Caicos Islands, Chad, Togo, Thailand, Tajikistan, Turkmenistan, Tonga, Trinidad and Tobago, Tunisia, Turkey, Uganda, Ukraine, Uruguay, Uzbekistan, Venezuela, Viet Nam, Vanuatu, Yemen, South Africa, Zimbabwe
2 ($n = 5$)	Andorra, Guam, Monaco, Puerto Rico, San Marino
3 ($n = 5$)	Bermuda, Barbados, Cameroon, Liechtenstein, Samoa
4 ($n = 1$)	Ireland
5 ($n = 5$)	Burma, Myanmar, New Zealand, United States, Zambia
6 ($n = 1$)	New Caledonia

Table 12: Countries and territories clustered together under HAC.

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