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Democracy clusters and patterns of inequality

A k-means approach

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Abstract: This paper employs k-means clustering, a multidimensional pattern recognition method, to categorize countries using information from five Varieties of Democracy indices. K-means country clusters are similar but not entirely identical to both k-medians clusters and arbitrary groups formed using only one measure, namely the liberal democracy index. Simple correlations with different inequality measures yield varying results. Despite having higher absolute inequality, country clusters with extremely high levels of democracy are characterized by lower relative inequality. They also have the lowest ratio of the income share of the richest 10 per cent to that of the poorest 40 per cent. K-means clusters with low- and medium-quality institutions generally do not differ much in terms of inequality outcomes.

Key words: clustering, democracy, inequality, pattern recognition

JEL classification: P00, C10, D63

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1 Introduction

Two concepts that are commonly discussed in the social sciences are inequality and democracy (Acemoglu 2001). Simply put, a democracy is a form of governance institution where the power is held by the people or by elected representatives. Inequality, meanwhile, is most often related to advancing social justice whereby everyone has access to basic needs and opportunities. Of relevance are a series of theoretical and empirical papers by Daron Acemoglu and his co-authors (Acemoglu 2010; Acemoglu and Robinson 2001; Acemoglu, Johnson and Robinson 2012; Acemoglu et al. 2015). In general, they show that democratic countries are more likely to put policies in place that support greater income equality, and that democracy leads to more income redistribution. Strong institutions may lead to more-progressive taxation that benefits the elite less. A paper by Hoff and Stiglitz (2004) suggests that equal income distribution also encourages improvements to institutions. They note that the reason for this is that the poor acquire fairer levels of political power when they are more economically capable. Interestingly, Sonin (2003) has argued that the causality may go the other way. Low-quality institutions, such as those displaying rent-seeking, lack of transparency, and corruption, cause inefficiencies in redistribution biased towards the rich. Such a dual relationship has been investigated by Chong and Gradstein (2007). They argue that while income inequality increases because of unfair institutions controlled by rich elites, the reverse can be true: weak quality of institutions leads to worse outcomes in terms of inequality. Their data analysis found that high levels of income inequality and poor institutions reinforce each other's adverse effects. These studies show that democracy and inequality are characterized by a feedback effect that is not necessarily straightforward.

Given the dynamics between inequality and institutions, it is relevant to clarify how these two variables are measured. First, note that democracy is a latent variable. It is not observable, and its quality can only be inferred indirectly using models from other observable variables. Thus, well-known one-dimensional democracy indices like those of Freedom House and Polity IV may not be sufficient to understand its characteristics (Gugiu and Centellas 2013). Taking all of this into account, the Varieties of Democracy (V-Dem) Institute has recently proposed five democracy indices: electoral democracy, deliberative democracy, participatory democracy, liberal democracy, and egalitarian democracy (Coppedge et al. 2023). The aim is to not summarize institutional quality into just one index. This allows researchers to capture and specify various characteristics of democracy depending on their needs. For our paper, the objective is not to combine the five V-DEM indices into one. What our work offers is an alternative approach to combining countries into categories (i.e. clusters) that are quantitatively determined. We follow closely and extend the methodology used by Huskinson and Lawson (2014): k-means cluster analysis. Clustering analysis can be used to categorize similar countries without relying on ad hoc solutions. That is, the clustering methodology provides an objective and quantitative approach to recognizing patterns in cross-country data. In creating country groupings based on democratic quality, it could be argued that we can simply use one of the one-dimensional indices (e.g. liberal democracy). We note, however, that countries that are similar in a one-dimensional value (i.e. liberal democracy) can be different in terms of underlying scores for the other V-DEM indices, e.g. electoral democracy. Using multidimensional clustering of countries will provide richer information.

Second, there is neither a single index that can underpin all aspects of income inequality, nor a particular dataset that contains comprehensive data to describe all measures of inequality. Income inequality has almost always been measured by the relative Gini coefficient. However, recent studies have shown that this may bias findings, and hence there is a need to consider other measures (Ravallion 2018). For example, it has been noted that global income inequality decreased in relative terms over the last 30 years. However, absolute inequality increased over the same period

(Nino-Zarazua, Roope, and Tarp 2017). As a solution, when describing differences in inequality levels among democracy clusters in this paper, we will use both measures, i.e. relative and absolute inequality.

To sum up, the paper aims to contribute in three ways:

1. It provides simple correlations of various democracy and inequality measures: using data from the World Income Inequality Database (WIID) database (UNU-WIDER 2023), we explore whether there are differences in the degree of relative and absolute inequality between countries with contrasting levels of institutional quality.
2. It uses disaggregated, multidimensional democratic quality data: taking advantage of the new V-DEM database (Coppedge et al. 2023), we define democratic institutions into five indices: electoral democracy, liberal democracy, egalitarian democracy, deliberative democracy, and participatory democracy. We will use these five institutional measures as instruments to categorize the 168 countries in our dataset.
3. It employs new methods for pattern recognition.

Overall, the aim of this research paper is to categorize the 168 countries in our sample by using k-means clustering methods (Huskinson and Lawson 2014). After forming different categories using various institutional measures, we provide a simple qualitative comparison of the inequality levels of these different democracy clusters. In doing so, we can describe whether countries with low vs high institutional quality (based on the five democratic indices above) have differences when it comes to levels of income inequality.

2 Related literature

In this section, we provide a brief overview of literature on the application of clustering methods in economics and related social sciences.

One of the earliest works on the use of k-means clustering in economics is by Crone (2005), on business cycles of US states. Based on the similarity of their business cycles, the states are divided into regions. To divide the 48 contiguous states into eight zones with similar economic cycle characteristics (e.g. cyclical components of Stock-Watson-type indices), Crone uses k-means cluster analysis of the indices calculated at the state level. He chooses to categorize the states into non-hierarchical, partitional clusters because he does not believe that the states have any hierarchical relationship in terms of business cycles. The new state clusters were compared with the arbitrary grouping of the Bureau of Economic Analysis (BEA). BEA has divided US states into eight areas since the 1950s, largely on the basis of similarities in cross-sections of their socioeconomic characteristics. But this grouping is arbitrary and merely descriptive, not based on quantitative analyses like k-means clustering. Cron (2014) argues that the state clusters in his paper, i.e. newly formed k-means clusters based on similarities in business cycle characteristics, are more useful than the arbitrary groupings offered by BEA. Most similar to this paper is the methodology demonstrated by Huskinson and Lawson (2014). In their research work, they categorize countries based on data from the five categories of the Economic Freedom of the World (EFW) index using k-means clustering. Precisely, they group countries using the five indices of EFW: size of government, legal system and property rights, sound money, freedom to trade internationally, and regulation. Their clustering results show that social democratic market economies do better than liberal market economies. They posit that the social democracy that we see today may be the result, rather than the cause, of the higher incomes and social trust generated by the economic freedom of years past. Another paper that is among the closest to our work is that of Aldrich et al. (2007), which also provides an application of k-means clustering to their investigation of pro-environmental attitudes. In order to account for unobserved heterogeneity, they evaluate the significance and reliability of cluster analysis in terms of environmental economics research. They do so in the context of gauging people's behaviour towards the environment. They find that substantial disparities exist among clusters in willingness to pay for environmental conservation, and that such heterogeneity among clusters could be helpful in improving the performance of predictive regression models in the future. Meanwhile, as one of their numerous analytical tools, Webber and Mearman (2012) use k-means clustering to study how students perceive economics as a field of study. Their article seeks to determine whether there is a distinct group of students who are interested in studying economics further. Using a dataset of student perceptions of economics from respondents all over the world, they classify distinct student clusters. They identify that there is an extremely small cluster of students who appear to be more open to further study. Their paper concludes by recognizing the need to focus research resources on more-effective economics and mathematics teaching so that students do not perceive the subject as too difficult. Finally, an application of k-means clustering to psychology, precisely perfectionist personality profiles, is offered by Bolin et al. (2014). They consider scenarios when population groups overlap or are unclear. They argue that a newer method from computer science, fuzzy clustering, permits an observation to be a member of numerous groups at once. The logic and methodology are the same as k-means clustering, where the centroid is the average. The only difference is that an observation can be a member of two clusters. In their paper, the cluster solutions of Bolin et al. (2014) are produced using both fuzzy clustering and k-means clustering to illustrate and compare the two approaches. The findings of these analyses show that the two approaches produce distinct cluster solutions, and the degree of similarity between the various clustering solutions relies on the amount of cluster overlap that fuzzy clustering allows for.

The use of k-medians clustering, in comparison, is rare in economics and other social sciences. Only a few papers have utilized k-medians clustering as an approach to categorize countries or people. Szente and Benedek (2022) is an example of recent attempts to explore k-medians analysis in the social sciences. They characterize the impact of COVID-19 on lifestyle-related choices and personal values of a representative sample of Hungarian consumers. A questionnaire was developed to analyse changes in food consumption and exercise habits after the COVID-19 outbreak in Hungary. They identify consumer clusters based on levels of impulsivity and food obsession. In their k-medians analysis, they take note of what is labelled a 'home-based' cluster of individuals who reduced frequency of eating and exercise-related activities. Those in this cluster appear to be most in need of psychological support to maintain their mental health. The authors add that since a sedentary lifestyle appears to be accompanied by a reduction in food intake, this group maybe less susceptible to the negative effects of obesity. Further exemplifying the potential use of k-medians cluster analysis, Gu et al. (2020) investigate the diverse effects of high-tech industry on carbon emissions in areas with heterogeneous levels of high-tech industry development. Their work examines the impact of China's high-tech industry growth on carbon emissions between 2005 and 2016. Using the k-medians cluster approach, they disaggregate the effects into areas with high, middle, and low levels of high-tech industrial development.

As a complement to the k-means and k-medians approaches, a similar tool called hierarchical clustering is also worth discussing. The logic of hierarchical clustering is similar to that of k-means analysis. The main difference lies in the assumption that the clusters are organized hierarchically from top to bottom. Each cluster is composed of several smaller sub-clusters. Hierarchical clustering views the entire dataset as one large cluster, with the sub-clusters within it acting as the parent cluster's partitions. A cluster with just one data point will be the smallest unit. The outcome of hierarchical clustering is a dendrogram, where nested clusters are organized as a tree (Neff and Pickard 2021). The advantage of k-means analysis as opposed to hierarchical clustering is that k-means analysis is more user friendly and straightforward. Results from k-means clustering are less arbitrary than the dendrogram trees of hierarchical clustering, which are often misinterpreted. Nonetheless, there have been papers showing the potential of hierarchical clustering in categorizing countries in terms of the quality of democratic institutions. An example of an article that employs hierarchical clustering techniques is Gugiu and Centellas (2013). They argue that democracy is a latent variable that is not easily observable and can only be inferred indirectly via a mathematical model from other observable variables. Because of this, they propose to create a new measure of democracy called the Democracy Cluster Classification (DCC) index. They create this new measure using hierarchical analysis of well-known democracy indices such as those of Freedom House and Polity IV. They do so with data observations from about 60 countries. In a similar vein, Ahlborn and Schweickert (2019) employ hierarchical clustering to identify types of economic systems in a sample of 115 developing and industrialized countries on the basis of aggregate policy variables and macroeconomic performance variables such as innovation capacity, income inequality, and public debt.

The main difference of our paper with the past democracy literature above is that we use k-means clustering instead of hierarchical clustering. K-means clustering provides a quantitative approach that is more objective and is not prone to misinterpretation. A profound disadvantage of hierarchical analysis as opposed to k-means clustering is that there are no standard criteria to set where clustering should happen. In hierarchical analysis, clusters are formed using a method by which the researcher arbitrarily imposes a line across the graph (i.e. tree dendrogram) and is thus prone to subjective decisions (Wolfson, Madjd-Sadjadi, and James 2004). In k-means analysis, on the other hand, clusters are produced using an iterative mathematical equation. Therefore, cluster groupings are more objectively determined. Another major difference, especially with Gugiu and Centellas (2013), is that we use democracy variables that are distinct from one another. While others use competing and highly similar democracy variables such as those of Freedom House and Polity IV, we specifically employ the five main V-DEM indices, which may differ vastly in their characteristics and the extent and type of democratic qualities that they measure, e.g. participatory democracy versus egalitarian democracy.

Differently from the clustering papers above, in the next sections we apply k-means clustering to investigate patterns and differences across democratic quality data. We then compare this with k-medians clustering, where the centroid of the cluster is the median value and not the mean. Finally, we describe simple patterns of income inequality across democracy clusters.

3 Methodology

3.1 Clustering

K-means is a tool that can be used to divide data into clusters or subgroups and describe within-cluster commonalities in characteristics, as well as between-cluster differences. The letter 'k' refers to the number of centroids needed for a given dataset. A centroid—an arbitrary measure—represents the centre of the cluster. Researchers can dictate the number of clusters (Huskinson and Lawson 2014). This is generally used in market segmentation research, e.g. classification or grouping of consumers according to age, income, tastes, etc. The general procedure is described below.

1. The researcher sets the number of clusters. Initial cluster centroids are formed by utilizing random selection for the k-clusters. The squared Euclidean distance is calculated based on the current cluster solution. Using this, we are able to organize the data into groups that

minimize the sum of the squared distances between the observations x and the centroid m inside each particular cluster S, clusters are mathematically identified. This can be summarized by the formula below.

$$\min \sum_{i=1}^{K} \sum_{x_j \epsilon S_i} x_j - \mu_i^2$$

2. Each observation (i.e. country) is re-designated to the cluster whose centroid it is most similar with.
3. The cluster centroids are updated after each reassignment. That is, steps 3–5 follow an iterative algorithm. The process is repeated until no further reassignment of country observations to clusters takes place, i.e., each country is in the cluster with the nearest centroid.

K-medians analysis follows a similar procedure. The main difference is that it is the median and not the mean which is the centre of the cluster. While k-means clustering uses the Euclidean distance measure (i.e. lowest possible distance between an observation and the centroid), k-medians clustering captures the Manhattan distance or the sum of all distances (e.g. vertical and horizontal distance) between the two points. In any case, k-medians and k-means clustering follow the same logic, except that k-medians centroids are less affected by the potential existence of outliers. They are both conducted to create categories of data. Those belonging to the same cluster has similar democracy scores. Two countries that belong to different clusters have different democracy scores, and are obviously not categorized into one cluster together. Overall, for our study, country-level observations with similar institutional quality, based on five democracy indices, are grouped together into one cluster. Each cluster differs significantly in its characteristics (i.e. the five democracy indices differ across categories or clusters formed).

3.2 Empirical strategy

We conduct clustering analyses using codes from the Stata package on k-medians and k-means analysis (Judson 1998). Our five clustering variables are the democratic institutions data from V-DEM. The five high-level V-Dem democracy indices are used to categorize the countries in our sample. These five variables are scaled between 0 and 1, with lower values pertaining to poorer institutional quality (Coppedge et al. 2023).

1. The electoral democracy index indicates the quality of voting rights and the degree of electoral competition. It covers whether elections are fraudulent or not, whether there is freedom of association, whether government officials are elected, and whether all citizens have the right to suffrage.
2. The participatory democracy index emphasizes political participation. That is, it is concerned with the possibility of building subnational elected bodies and whether civil society engagement exists.
3. The egalitarian democracy index is about how socioeconomic inequalities hinder democratic freedoms. Egalitarian democracy is dependent on the equal protection of political freedoms of citizens across all social groups. Furthermore, it requires equal distribution of economic resources.
4. The liberal democracy index is measured by emphasizing the protection of individual rights against autocrats. The main measure for this variable is whether real limits to government power exist. These include checks and balances in the government, constitutional protection of civil rights, rule of law, and autonomy of the judicial system.

5. The deliberative democracy index is a variable that relates to the possibility of respectful dialogue within a country's government—that is, a situation where public decision-making is not characterized by one-sided interests.

After the 168 countries are categorized using the five V-DEM democratic indices as clustering variables, we then describe the absolute inequality, relative inequality, and Palma ratio of the different clusters. Absolute inequality is defined as the relative Gini coefficient (i.e. the standard measure of relative inequality) multiplied by the GDP of the country. The Palma ratio, meanwhile, is the share of total income received by the top 10 per cent of the population, with the most disposable income, divided by the percentage of total income received by the poorest 40 per cent. We use data from the World Income Inequality Database (WIID; UNU-WIDER 2023). Because traditional k-means clustering analysis can only be used for a cross-section of countries and is not feasible for time series data, we average all variables (e.g. institutions and inequality) from the most recent data, 2011–20. Averaging data also mitigates the risk of results being affected by outliers, shocks, or other business cycle effects. It gives a measure that is more stable over a given period. This allows the k-means and k-medians analysis to have the highest possible sample size of 168 countries. Had we chosen a larger timeframe, inequality data from the WIID database (UNU-WIDER 2023) would greatly reduce our sample size to less than 50 per cent, and so we posit that the ideal time range is 2011–20, as during this range there are more countries with more available continuous data. Each of the 168 countries will have one data point or observation for the clustering exercise.

4 Results

4.1 Main analysis: k-means clustering

With 168 country data observations, we cluster according to the five democracy variables: electoral democracy, liberal democracy, egalitarian democracy, deliberative democracy, and participatory democracy. Below, I start the analysis with k-means clustering.

We considered the possibility of having either two, three, or four clusters. The criteria of three clusters or categories was chosen, because it has the highest Calinski-Harabasz pseudo-F score of 612. This is a tool that helps determine cluster sizes. Mathematically, it is the ratio of the sum of between-clusters variance and of inter-cluster variance for all clusters. In simple terms, a higher score indicates that clusters are well separated and dense, i.e. different clusters have a high degree of variance. We also found that if two clusters are chosen, the value is 474. For four clusters, it is 606. The 168 countries in the sample are thus categorized into three clusters. We label the three clusters as follows:

- Cluster 1: low institutional quality
- Cluster 2: medium institutional quality
- Cluster 3: high institutional quality.

We now describe and compare the average values of the three clusters' five indices and levels of relative and absolute inequality. Following the V-DEM database, the five variables for the quality of democracy are labelled as follows:

- poly: electoral democracy
- lib: liberal democracy
- partip: participatory democracy

- delib: deliberative democracy
- egal: egalitarian democracy

Measures of relative and absolute inequality are respectively labelled as *gini* and *ginia* in the discussion below. Following scaling from the WIID, Gini values range from 0 to 100, with those nearer 0 having low inequality and those closer to 100 characterized by high levels of income inequality. The absolute Gini coefficient, *ginia*, has a larger range because absolute levels of inequality are calculated as the relative Gini multiplied by the country's GDP (UNU-WIDER 2023).

We observe that countries in K-Means Cluster 1 are characterized by low democracy scores across the five indices. The average score for electoral democracy is 0.26. Other measures for democratic institutions exhibit lower mean scores. Participatory democracy and liberal democracy are at 0.14 on average. Deliberative democracy and egalitarian democracy both have an average score of approximately 0.17 on average for the 65 countries under K-Means Cluster 1 (see Table 1).

Table 1: K-Means Cluster 1—low institutional quality

	Mean	Median	Min.	Max.	N
vdem ave 2020	0.179	0.184	0.048	0.298	65
poly	0.264	0.263	0.017	0.468	65
lib	0.149	0.138	0.007	0.334	65
partip	0.143	0.148	0.009	0.267	65
delib	0.167	0.156	0.009	0.321	65
egal	0.172	0.182	0.073	0.294	65
gini	44.306	42.726	0.000	65.642	65
ginia	517.499	262.402	0.000	3,403.696	65
gdp	13,103.317	6,070.108	811.635	93,601.969	65
palmaratio top10o~40	2.894	2.175	0.250	9.132	65

Source: author's own construction based on V-Dem data.

Further inspection of descriptive statistics in K-Means Cluster 1 shows that average levels of income inequality in these countries are relatively high. The mean value for relative inequality, *gini*, is at 44, while that of *ginia*, absolute inequality, is also at a high value of 517.

The average levels of inequality for K-Means Cluster 1 are similar to those found in K-Means Cluster 2. Relative and absolute income inequality were observed to have mean scores of 46 and 449, respectively. While countries in K-Means Cluster 2 have similar relative inequality scores to those in K-Means Cluster 1, they have slightly lower levels of absolute inequality. Furthermore, there are significant differences between K-Means Cluster 1 and K-Means Cluster 2 when it comes to their quality of democratic institutions (see Table 2).

Table 2: K-Means Cluster 2—medium institutional quality

	Mean	Median	Min.	Max.	N
vdem ave 2020	0.427	0.416	0.306	0.558	52
poly	0.563	0.581	0.399	0.714	52
lib	0.417	0.43	0.233	0.587	52
partip	0.35	0.361	0.106	0.489	52
delib	0.425	0.421	0.275	0.602	52
egal	0.38	0.364	0.249	0.537	52
gini	46.582	46.778	28.577	67.493	52
ginia	449.538	351.437	57.973	3,637.516	52
gdp	10,595.028	8,121.303	1,142.245	90,455.172	52
palmaratio top10o~40	3.211	2.689	1.026	10.243	52

Source: author's own construction based on V-Dem data.

For K-Means Cluster 2, the scores for the five democracy variables are two to five times greater than those of countries categorized at K-Means Cluster 1. On average, there is a jump in electoral democracy scores to around 0.563. Liberal democracy and deliberative democracy follow a similar pattern to each other, with mean values of 0.417 and 0.425 for the 52 countries categorized into K-Means Cluster 2. Participatory democracy and egalitarian democracy have slightly lower scores at 0.350 and 0.380 respectively, but they are twice as high as those for K-Means Cluster 1 counterparts.

Finally, a high degree of quality in terms of democratic institutions is exhibited by the 51 countries categorized under K-Means Cluster 3 (see Table 3).

Table 3: K-Means Cluster 3—high institutional quality

	Mean	Median	Min.	Max.	N
vdem ave 2020	0.725	0.748	0.585	0.851	51
poly	0.835	0.851	0.694	0.92	51
lib	0.751	0.775	0.558	0.889	51
partip	0.588	0.617	0.340	0.8	51
delib	0.734	0.741	0.566	0.874	51
egal	0.715	0.744	0.507	0.871	51
gini	37.726	34.332	25.988	67.236	51
ginia	1,247.098	1,216.14	112.799	3,770.994	51
gdp	36,341.399	36,717.004	3,016.453	113,974.72	51
palmaratio top10o~40	2.032	1.373	0.898	10.253	51

Source: author's own construction based on V-Dem data.

Compared with K-Means Cluster 1 and K-Means Cluster 2, the 51 countries categorized under K-Means Cluster 3 are characterized by extremely high scores for all five democracy variables. This is reflected in an average score of 0.835 in terms of electoral democracy. Participatory democracy takes a comparably lower score of 0.587. The other measures of democracy have mean scores hovering around 0.7: egalitarian democracy 0.714; deliberative democracy 0.733; and liberal democracy 0.750.

Those countries under K-Means Cluster 3 also have much lower levels of relative income inequality than those in K-Means Cluster 1 and K-Means Cluster 2. The average value for *gini*, at 37.7, is about seven points lower than those of other clusters. However, this comparably lower level of relative income inequality is not reflected in absolute inequality. What we found is the opposite. Compared with other clusters, K-Means Cluster 3 has the highest level of absolute inequality, *ginia*, at 1,247. This is more than double the absolute income inequality levels found in the other two clusters in our study.

As a complement to relative and absolute measures of inequality, we also considered the Palma ratio, or the ratio of the richest 10 per cent of the population's share of national income to that of the poorest 40 per cent. We find an interesting non-linear correlation. Those in the medium democracy clusters were found to have the highest Palma ratio and therefore the highest level of inequality. Those grouped in Cluster 3, with the highest level of institutional quality, were found to have the lowest inequality in terms of the Palma ratio.

We synthesize the main observations below.

- Countries can be grouped into three non-arbitrary categories using five V-DEM variables: electoral democracy, egalitarian democracy, participatory democracy, liberal democracy, and deliberative democracy.
- The three clusters produced are characterized by either low, medium, or high quality of democratic institutions.
- The three clusters significantly differ in terms of level of democratic characteristics. However, only those with extremely strong institutions exhibit a huge difference in terms of absolute and relative inequality levels. Those with good institutions are characterized by lower levels of relative income inequality.
- But this does not translate to lower absolute inequality. Instead, we observed a paradoxical pattern. Countries characterized as having the best quality of democratic institutions tend to have higher absolute inequality levels, despite having lower relative inequality scores.
- When comparing the share of the top 10 per cent and the bottom 40 per cent of the population, we find those with medium levels of democratic quality to be worst off. Those with the best institutions are better off in terms of inequality. They have the lowest ratio when it comes to the relative shares of the richest 10 per cent and the poorest 40 per cent.

Overall, the conclusion of this research paper is that good institutions are correlated with lower relative inequality levels. However, because the countries with good democracy levels tend to be those with higher incomes too, they tend to suffer from higher absolute inequality compared with those with poorer institutions. In summary, the association between the quality of institutions and inequality only becomes apparent when the quality of institutions is sufficiently high. When the quality of democracy is high enough, we can see a clear correlation between strong institutions and lower relative inequality. This does not translate, however, to lower absolute inequality. In fact, what is observed is the opposite. For obvious reasons, nonetheless, the simple correlations and comparison of descriptive statistics (e.g. average as the cluster centroid) discussed above should not be over-analysed. There are numerous confounding factors, and establishing causal links necessitates far more investigation. That, however, is beyond the specific aims and scope of this paper.

4.2 Supplementary analyses

In the next subsections, I provide country groupings from k-medians clusters and compare them with those in the k-means analysis. I also give a brief example of how k-means clusters differ from groupings established in an ad hoc manner.

K-medians clustering

To contrast the results, we also use three categories for k-medians analysis. Descriptive statistics for the three k-medians clusters are presented below. The main difference in the analysis is that k-medians clustering uses the median as the centroid instead of the mean. So, in our discussion below, we focus on the medians of the democracy clusters.

Looking closely at the three k-medians clusters, we observe similar patterns to those of k-means clusters. Using the five democracy variables, countries can be categorized into three groups:

- K-Medians Cluster 1: low institutional quality
- K-Medians Cluster 2: medium institutional quality
- K-Medians Cluster 3: high institutional quality

Those in K-Medians Cluster 1 have a median score of 0.271 for electoral democracy. Although this sounds optimistic, these countries are, however, characterized by lower median values of 0.141, 0.150, 0.168, and 0.185 for liberal democracy, participatory democracy, deliberative democracy, and egalitarian democracy respectively. Their average scores for the five V-DEM indices also follow a similar trend and are approximately the same as the median values (see Table 4).

Table 4: K-Medians Cluster 1—low institutional quality

	Mean	Median	Min.	Max.	N
vdem ave 2020	0.187	0.196	0.048	0.316	69
poly	0.273	0.272	0.017	0.468	69
lib	0.156	0.142	0.007	0.334	69
partip	0.147	0.151	0.009	0.286	69
delib	0.176	0.169	0.009	0.361	69
egal	0.181	0.185	0.073	0.355	69
gini	44.852	43.383	0.000	65.642	69
ginia	545.408	261.449	0.000	3,637.516	69
gdp	13,743.738	5,453.501	811.635	93,601.969	69
palmaratio top10o~40	2.988	2.233	0.250	9.132	69

Source: author’s own construction based on V-Dem data.

Furthermore, the countries under K-Medians Cluster 1 are characterized by moderate levels of relative inequality. The average *gini* value is 44.85, while the median value is 43.38. There is a great discrepancy, however, in the mean and median values for absolute inequality, *ginia*. The average level of absolute income inequality is 545, but the median level of absolute inequality is 261. This could indicate the effect of outliers in the data. Upon close inspection, we can see that the range of absolute inequality values is large: from 0 to 3,637 units.

We observe similar patterns for relative inequality for those countries under K-Medians Cluster 2 (see Table 5). Both the mean and the median scores for this variable are at 46, a value that is not significantly different from that found under K-Medians Cluster 1, i.e. 44. There are differential values too in the levels of absolute inequality. The median value is at 374, while the average is 445.

Table 5: K-Medians Cluster 2—medium institutional quality

	Mean	Median	Min.	Max.	N
vdem ave 2020	0.454	0.46	0.324	0.603	54
poly	0.592	0.6	0.426	0.749	54
lib	0.45	0.449	0.255	0.645	54
partip	0.371	0.366	0.205	0.489	54
delib	0.454	0.444	0.275	0.65	54
egal	0.405	0.397	0.249	0.594	54
gini	46.277	46.225	28.577	67.493	54
ginia	445.26	374.748	57.973	1,499.668	54
gdp	10,236.265	10,085.513	1,142.245	37,835.207	54
palmaratio top10o~40	3.202	2.618	1.026	10.253	54

Source: author's own construction based on V-Dem data.

What makes K-Medians Cluster 2 different from K-Medians Cluster 1 is the difference between the two groups of countries in the quality of the institutions. For those in K-Medians Cluster 2, electoral democracy scores have an average and median value of 0.59. Participatory democracy has the lowest index, at 0.37. Egalitarian democracy, liberal democracy, and deliberative democracy have median scores of 0.397, 0.449, and 0.444 respectively. Average values follow the same pattern. All in all, K-Medians Cluster 2 is characterized by moderate quality of institutions, throughout the five democracy variables.

Stark discrepancies are further observed for those countries under K-Medians Cluster 3 (see Table 6). Those in this group have extremely strong quality of democratic institutions. Mean and median scores for the five V-DEM indices are almost equal. Electoral democracy has a median value of 0.868. Liberal democracy, deliberative democracy, and egalitarian democracy are at 0.787, 0.75, and 0.764 respectively. Meanwhile, the participatory democracy score for K-Medians Cluster 3, at 0.606 for the average and a median of 0.625, remains higher than for those at K-Medians Cluster 1 and K-Medians Cluster 2.

Table 6: K-Medians Cluster 3—high institutional quality

	Mean	Median	Min.	Max.	N
vdem ave 2020	0.742	0.758	0.617	0.851	45
poly	0.849	0.868	0.757	0.92	45
lib	0.769	0.787	0.597	0.889	45
partip	0.606	0.625	0.340	0.8	45
delib	0.749	0.75	0.582	0.874	45
egal	0.736	0.764	0.507	0.871	45
gini	36.276	33.224	25.988	57.614	45
ginia	1,309.737	1,246.512	368.561	3,770.994	45
gdp	38,999.827	38,884.102	6,479.887	11,3974.72	45
palmaratio top10o~40	1.77	1.304	0.898	5.782	45

Source: author's own construction based on V-Dem data.

K-Medians Cluster 3 is characterized by comparably lower relative inequality. Relative *gini* values are at 36. This is similar to the values described under k-means clustering analysis: specifically, it is almost the same as those found under K-Means Cluster 3. We see that those with the highest quality of democratic institutions tend to have lower relative inequality, compared with counterparts who suffer from poorer institutions and higher relative inequality. What remains striking, unfortunately, is that this is also associated with greater absolute income inequality. For

K-Medians Cluster 3, the absolute inequality measure *ginia* has an average and median value of around 1,300, which is higher than those found in the other two clusters with poorer institutions.

Findings for the Palma ratio, meanwhile, follow the same pattern as those under k-means clustering. Countries with medium levels of democratic quality have the highest difference in terms of the income shares of the richest 10 per cent and the poorest 40 per cent. On the other hand, countries with the strongest level of democracy have the lowest median Palma ratio.

In terms of the three levels of institutional quality (low, medium, high), are there countries that do not overlap in their groupings in the k-means versus k-medians clusters? Yes: out 168 countries, around 10 were observed to have conflicting groupings. For instance, we found differential categories for Mozambique, Comoros, Singapore, and Togo. In the k-medians clusters they are classified as low in terms of democracy, but they are medium when k-means are used. Likewise, Ghana, Tunisia, Panama, Vanuatu, South Africa, and Israel were categorized as having high quality of democratic institutions under the k-means analysis but rated as medium under the k-medians clusters.

Arbitrary grouping

We look now at the results if we establish ad hoc groupings using one democracy measure only, instead of the five V-DEM indices. In this case, we use the liberal democracy index. We group countries into three categories (low, medium, high) based on their average ranking in terms of liberal democracy scores and compare them with those we found using multidimensional k-means clustering. The liberal democracy index is used because it is the main measure that V-DEM uses to rank countries in its annual reports (Coppedge et al. 2023). Each of the three categories contains 56 countries. Tables 7–9 summarize the descriptive statistics for the three arbitrary groupings.

Table 7: Group 1—low liberal democracy

	Mean	Median	Min.	Max.	N
vdem ave 2020	0.166	0.166	0.048	0.316	56
poly	0.248	0.25	0.017	0.444	56
lib	0.129	0.121	0.007	0.235	56
partip	0.133	0.131	0.009	0.286	56
delib	0.153	0.15	0.009	0.361	56
egal	0.17	0.162	0.073	0.341	56
gini	44.31	43.692	0.000	65.642	56
ginia	475.831	254.652	0.000	3,403.696	56
gdp	12,188.73	5,761.804	811.635	93,601.969	56
palmaratio top10o~40	2.964	2.262	0.250	9.132	56

Source: author's own construction based on V-Dem data.

Table 8: Group 2—medium liberal democracy

	Mean	Median	Min.	Max.	N
vdem ave 2020	0.389	0.392	0.225	0.545	56
poly	0.52	0.529	0.266	0.702	56
lib	0.381	0.373	0.236	0.551	56
partip	0.32	0.331	0.101	0.489	56
delib	0.386	0.39	0.217	0.581	56
egal	0.339	0.322	0.127	0.536	56
gini	45.607	44.905	28.577	67.493	56
ginia	494.417	340.546	57.973	3,637.516	56
gdp	11,918.306	7,993.396	1,142.245	90,455.172	56
palmaratio top10o~40	2.978	2.433	1.026	10.243	56

Source: author's own construction based on V-Dem data.

Table 9: Group 3—high liberal democracy

	Mean	Median	Min.	Max.	N
vdem ave 2020	0.708	0.73	0.530	0.851	56
poly	0.822	0.839	0.655	0.92	56
lib	0.734	0.757	0.553	0.889	56
partip	0.573	0.603	0.340	0.8	56
delib	0.717	0.729	0.528	0.874	56
egal	.695	0.73	0.446	0.871	56
gini	39.123	35.147	25.988	67.236	56
ginia	1,183.597	1,136.393	112.799	3,770.994	56
gdp	34,037.043	33,564.041	3,016.453	113,974.72	56
palmaratio top10o~40	2.25	1.432	0.898	10.253	56

Source: author's own construction based on V-Dem data.

Which countries do not overlap between the objectively determined k-means clusters and the ad hoc one-dimensional groupings? We observe several countries that are rated as high in terms of liberal democracy but are not rated as having strong institutions in the multidimensional k-means clustering; these are Namibia, São Tomé and Príncipe, Bulgaria, Botswana, and Senegal. There are also countries that are in the lowest ad hoc liberal democracy group but are not categorized as low in the multidimensional clusters; these are Morocco, Kuwait, Uganda, Haiti, Hong Kong, Malaysia, Honduras, Pakistan, Iraq, Guinea-Bissau, and Papua New Guinea. Finally, there are also countries that are grouped as medium in the ad hoc one-dimensional analysis but not in the k-means clustering: Namibia, Togo, Comoros, São Tomé and Príncipe, Bulgaria, Senegal, and Botswana.

For brevity, we now directly compare centroid values in Table 10. For k-means clustering and arbitrary groupings based solely on the liberal democracy index, the centroid is the overall average. The centroid for k-medians clustering is not the cluster mean but rather the median.

Table 10: Comparison across democracy clusters.

Variable of interest	All-sample average (N = 168 countries)	K-means centroid (mean)	K-medians centroid (median)	Arbitrary liberal democracy average
vdem_ave	0.421			
Low		0.179	0.196	0.166
Medium		0.427	0.46	0.389
High		0.725	0.758	0.708
libdem	0.415			
Low		0.149	0.142	0.129
Medium		0.417	0.449	0.381
High		0.751	0.787	0.734
gini	43.013			
Low democracy		44.306	43.383	44.31
Medium democracy		46.582	46.225	45.607
High democracy		37.726	33.224	39.123
ginia	717.949			
Low democracy		517.499	261.449	475.831
Medium democracy		449.538	374.748	494.417
High democracy		1,247.098	1,246.512	1,183.597
Palma ratio	2.73			
Low democracy		2.894	2.233	2.964
Medium democracy		3.211	2.618	2.978
High democracy		2.032	1.304	2.25

Source: author's own construction based on V-Dem data.

We define *Vdem_ave* as the average of all the five V-DEM indices. The overall sample average is 0.421, which is just below the middle of the 0–1 scale. The whole sample has an average of 0.415 for the one-dimensional liberal democracy index. The relative Gini index (*gini*) is 43, while the mean absolute Gini (*ginia*) is at 717. The average Palma ratio of the whole sample is 2.73. However, these values will vary depending on the tool used. We discuss these briefly below.

1. Aggregate multidimensional democracy scores and one-dimensional liberal democracy scores

Patterns for the k-means and k-medians clusters are relatively similar. Across all democracy levels, however, values for the ad hoc one-dimensional groupings have lower centroid values than those found under k-means and k-medians. For instance, those categorized as medium have a centroid V-DEM score of 0.389 in the ad hoc groups, but centroid scores of 0.427 and 0.46 in the clustered groups. When comparing across one dimension only, i.e. liberal democracy scores, we find the same observation. Those categorized as medium in the ad hoc groups are at 0.38, while for k-means and k-medians the scores are at 0.42 and 0.44 respectively.

2. Income inequality

Centroid values for relative inequality (i.e. the Gini coefficient) are profoundly similar, but not entirely identical, across all the three grouping types. Stark differences are observed with the relative inequality measure, however. Consider first the countries grouped as having weak democratic institutions across the three methods. We see that for k-medians clustering, the centroid value for absolute inequality is 261. This is compared with values of 517 and 475 respectively using the k-means and ad hoc method. This is not surprising, because k-medians clustering take into account the impact of outliers in its analysis while the other two methods take the mean as the centroid. This pattern is further seen when considering medium democracy groups. Absolute Gini is at 374 for the k-medians medium cluster, but around 400–500 for k-means and the arbitrary grouping. Lastly, for the Palma ratio, we find that scores are always highest in the ad hoc grouping, and lowest for the k-medians clusters.

Ultimately, the association between inequality and democracy is not clear-cut across the three methods. Despite lower absolute inequality, country clusters with exceptionally low levels of democracy have higher relative inequality. They also have the highest income ratio of the richest 10 per cent to the poorest 40 per cent. In terms of inequality outcomes, there is no difference between k-means clusters with low- and medium-quality institutions. Only when the quality of democratic institutions is high does relative inequality exhibit a large decrease in value.

5 Conclusions

We have provided a concise discussion on how country groupings can be obtained from k-means clustering of multidimensional democracy data. We characterize simple correlations of these k-means democracy clusters with different inequality measures, such as Gini and the Palma ratio. We find that the results are not entirely identical to those obtained using one-dimensional country groupings or k-medians clustering.

There are several avenues to extend our research. In the future, k-means clustering analysis could complement standard econometric regressions. It could be used to group similar countries without relying on ad hoc criteria. Each country cluster could be designated an indicator variable in the regression. This could be used to compare whether the impact and significance of results differs across clusters. Another possible extension would be the analysis of how cluster groupings change over time. Changes in democracy clusters might be apparent across decades, and are to be expected because the type of government and levels of development will vary over time. Thus, the number of clusters and memberships of countries within each cluster may change over a longer period.

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Appendix: Country groupings from k-means clustering

Table A1: K-Means Cluster 1—low

Country
Korea, DPR
Eritrea
Saudi Arabia
Syria
Turkmenistan
Bahrain
China
Qatar
United Arab Emirates
Equatorial Guinea
Tajikistan
Laos
Azerbaijan
Uzbekistan
Eswatini
Somalia
Sudan
Yemen
Egypt
Oman
Burundi
Chad
Kazakhstan
Cambodia
Iran
Congo, Republic of the
Djibouti
Belarus
Ethiopia
Angola
Bangladesh
Venezuela
Russia
Thailand
Vietnam
Nicaragua
Rwanda
Cameroon
Congo, Democratic Republic of the
Jordan
Central African Republic
Zimbabwe
Algeria
Guinea
West Bank and Gaza
Libya
Morocco

Fiji
Gambia, The
Kuwait
Mauritania
Afghanistan
Uganda
Madagascar
Turkey
Myanmar
Haiti
Hong Kong
Malaysia
Honduras
Pakistan
Iraq
Guinea-Bissau
Papua New Guinea
Gabon

Source: author’s own construction.

Table A2: K-Means Cluster 2—medium

Country
Singapore
Mozambique
Comoros
Togo
Maldives
Zambia
Ukraine
Kyrgyzstan
Tanzania
Lebanon
Armenia
Serbia
Mali
Kenya
Albania
Dominican Republic
Côte d’Ivoire
Seychelles
Sri Lanka
Philippines
Sierra Leone
Guatemala
Paraguay
Nigeria
Malawi
Solomon Islands
Nepal
India
El Salvador
Ecuador

Guyana
Mexico
Liberia
Bolivia
Niger
Lesotho
Timor-Leste
Hungary
Moldova
Bhutan
Burkina Faso
Benin
Colombia
Georgia
Indonesia
Namibia
Mongolia
São Tomé and Príncipe
Bulgaria
Romania
Botswana
Senegal

Source: author’s own construction.

Table A3: K-Means Cluster 3—high

Country
Tunisia
Panama
Ghana
Vanuatu
Israel
South Africa
Barbados
Suriname
Argentina
Trinidad and Tobago
Peru
Mauritius
Cape Verde
Brazil
Malta
Poland
Jamaica
Korea, Republic of
Taiwan
Latvia
Canada
Japan
Cyprus
Lithuania
Czechia
United States

Slovenia
Chile
United Kingdom
Greece
Austria
Spain
Iceland
Ireland
Netherlands
Australia
Estonia
Italy
France
Finland
Luxembourg
Portugal
Belgium
New Zealand
Germany
Uruguay
Norway
Costa Rica
Sweden
Denmark
Switzerland

Source: author's own construction.