Facultad de Ciencias Económicas y Empresariales
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Heterogeneity In Economic Freedom: Free Clusters Or Free Countries?

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ABSTRACT
How heterogeneous are countries with respect to economic freedom? This is an interesting empirical question since, if we can discover different groups of countries according to their economic freedom indicators, we will be able to identify which steps are required to foster convenient institutional changes. To come up with an answer to this question, we apply a hybrid clustering method - HOPACH - to two sets of components of economic freedom. These two datasets, which account for heterogeneity among countries, are built on the same information framework but with different degrees of aggregation. Specifically, we work on both the 38 variables and the five major areas of the Fraser Institute's Economic Freedom of the World Index. In both cases, HOPACH produces a segmentation and an ordered list of countries. Our results suggest that the classification of countries based on an overall economic freedom index may take us to misleading conclusions due to multidimensional sources of heterogeneity and the uncertainty about the number of segments in the distribution of the index.

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1 Introduction.

Institutional features have become a key ingredient in most theories of economic growth and human development, whose empirical validation requires data on institutional quality. At the same time, countries are increasingly interested in diagnosing institutional failures as a first step towards appropriate reforms. Both developments have converged in a new interest in quantifying qualitative institutional aspects. Academic centers, think-tanks and international agencies are among the growing number of organizations that publish indicators of institutional quality.

All such indicators try to encapsulate unobservable characteristics in a summary index by taking the information contained in observable variables. This is an standard practice in a wide range of research fields in social sciences, including economics. A good example is the Consumer Confident Index, an index based on a survey of about 5,000 households. The index considers consumer opinion on both current conditions (40% of the index) and future expectations (60%). The unobservable variable is consumer optimism, and the observable numbers are the survey answers. This index attracts great attention because many economists consider consumer optimism an advanced indicator, even a determinant, of the future health of the economy. Many questions must be weighed and included because no single item can measure optimism perfectly. Some questions are thought to tell more about consumer optimism than others and consequently deserve greater weight.

Attempts to measure economic freedom deal with analogous difficulties. Economic freedom is a concept that everyone understands but no one can observe. In fact, there is no single unanimously accepted definition. This is not just a semantic quibble, because how economic freedom is defined ends up affecting what actually gets measured and tested. Economic freedom is on the basis of the market economy system. It is inextricably connected to the right of individuals to pursue their interests through voluntary exchange under a rule of law that guarantees private property. For some scholars (e.g. de Haan, 2003), it is something completely distinct from political or civil liberties.

Others hold the opposite point of view, like Friedman (2002), who calls for constructing a combined measure of economic and political freedom, putting both on the same philosophical basis.

In spite of such disagreements, social scientists believe that economic freedom has much to do with various institutional attributes, which in turn might be highly correlated with observable variables, such as tax rates, tariffs, public expenditure or responses to surveys. In other words, they treat economic freedom as a latent concept with multiple indicators. Each indicator summarizes, at least to some extent, an important aspect of economic freedom. All the indicators are supposedly correlated with the latent variable, though the degree of correlation is different across components.

Indexes like those constructed by the Fraser Institute and the Heritage Foundation, which aim to capture the degree of economic freedom in a single number, take that approach. They collect, process and add information about a broad array of institutional factors that allegedly determine economic freedom. Each factor is graded according to a unique scale. Then each country gets its summary index based on some weighting of the individual factor scores -both the Heritage Foundation and the Fraser Institute use simple averages-. This seems a reasonable approach, although several questions remain unanswered. Which factors should be included? Is it possible to quantify them? How much information does each factor provide about the degree of economic freedom? Can we combine all the factors into a single and meaningful index? There is not always a sound theoretical reason to reject or accept that a variable is highly related to economic freedom. And a priori hypotheses about how important each component is to economic freedom can prove to be wrong.

All the above considerations are relevant because indexes are used in research as proxies to the very concept of economic freedom. One of the main benefits of having indicators for economic freedom is that they enable researchers to test whether economic freedom is related to variables of interest. And research results can become the guidelines to political and institutional reform. Any bias, omission or error in the index construction could lead to wrong conclusions about the role that economic freedom plays in shaping the institutional framework more conducive to human development and welfare.

In this paper we do not intend to create a brand new, more precise index. We work on an existing and publicly available index: The Economic Freedom of the World index (EFW index), published by the Fraser Institute. We try to get a better picture of economic freedom by using the information provided by the index components and subcomponents instead of relying only on the overall index. That is, we admit that variables were correctly chosen by the authors in their attempt to collect the relevant information. We agree all components describe key institutional and policy features. Each of them explains an aspect of a multidimensional value. But, as Caudill et al. (2000) pointed out, it is questionable that a concept as elusive as economic freedom can be quantified in a single index.

Under such assumptions, the logic behind our analysis is that variability in the components and relations between them contain information that can be used in a more efficient way. We should take that information into account in order to get an improved snapshot of institutional differences between countries and a more reliable explanation of the forces working behind economic performance across countries.

Here, we are interested in economic freedom ratings and rankings, as well as the way they allow to classify countries into different groups. Everybody -companies, investors, governments, institutions, media,...- cares about rankings. Citizens want their countries to be at the top of the countless lists (e.g., most competitive economies, least corrupted nations, most democratic governments,...). But institutional quality rankings are useful only as long as they provide policy makers with clear signals about where their countries are and which countries of higher ranking they could try to imitate. The issue is whether rankings of economic freedom are an accurate picture of each country's relative situation.

The remainder of this paper is organized as follows. The second section presents a detailed description of the methodology behind the construction of the EFW Index. The third section deals with the statistical nature of the Fraser´s dataset. It includes a

Multidimensional Scaling analysis that allows a visual representation of the heterogeneity among countries concerning their economic freedom features. Sections four and five are devoted to a deeper study of such heterogeneity through HOPACH, a recently developed clustering method whose main characteristics and properties are explained before its implementation. The final section consists of some concluding remarks.

2 The Fraser Index.

Different economic freedom indicators have been created during the last 15 years, since the seminal paper by Scully and Slottje (1991). Messick (1996) constructed an index for Freedom House, although his study has never been updated. The Heritage Foundation, jointly with the Wall Street Journal, has published an index of economic freedom on a yearly basis since 1995. But one of the most successful indicators of institutional quality, at least to our knowledge, has been the EFW index published by the Fraser Institute since 1996. Many empirical analyses rely on this index because it covers a wider span of time than any other indicator. It could arguably be said to provide more precise and transparent information, even though it does not include as many countries as the Heritage index.

In the latest version of the Economic Freedom of the World Report (Gwartney and Lawson, 2004), the Fraser index is made up of 38 distinct pieces of data, including survey data (18 variables) and hard data (20 variables). These variables are grouped to form 21 components which are incorporated into the five major areas of the index: a) Size of Government; b) Legal Structure and Security of Property Rights; c) Access to Sound Money; d) Freedom to Trade Internationally; and e) Regulation of Credit, Labor, and Business.

The 2004 EFW index is available for a sample of 123 countries, although many of them lack data on some of the 38 variables. The data set is complete only when we consider both the summary index and its major five areas. The missing data problem is more severe for the survey variables. These omissions are especially important in two areas -Legal Structure and Security of Property Rights, and Regulation of Credit, Labor, and Business- and, to a lesser degree, in Freedom to Trade Internationally, so that the authors recommend that comparisons between countries should be done with caution.[1]

Each component and each variable is assigned a value on a scale from 0 (no freedom at all) to 10 (complete freedom) that reflects the distribution of the underlying data within the complete country sample. One of the methodological questions that the Fraser Institute has had to tackle over the years is how to assign weights to various components and areas to compose a summary index. They have experimented with several different weighting methods. In the original publication (Gwartney et al., 1996), they constructed three summary indexes based on alternative methods of weighting. The weight for each component in the first index was equal to the inverse of its standard deviation. In the second one, weights were determined according to the opinions of a group of experts. Finally, in the third index, an equal weight was assigned to each component. More recently, in the 2001 version of the index, principal components analysis was used in an attempt to derive a more objective weighting arrangement.

The choice of the weighting method seems to have little influence on the rating of countries (de Haan, 2003). Consequently, Gwartney and Lawson (2004) keep the simplest procedure. That is, they use a nonweighted average to combine the components into area ratings and the area ratings into summary ratings. This procedure does not mean that all components and areas must be treated as equally important for economic freedom. Gwartney and Lawson (2004) themselves invite researchers to rebuild the weighting structure according to how important each component or area is for their purposes.

The study of economic growth is one of those possible purposes. The EFW index -as well as other indicators of freedom- has been extensively used in the research about the relationship between economic freedom and growth. This does not come as a surprise, since the concept of economic freedom is at the heart of the invisible hand theory, which establishes a causality relation, working through the free market system, between

[1] We were informed by one of the authors of the EFW that the main determinant of including or excluding a country had to do with the availability of a "critical mass" of data.

individual's own interest and public prosperity. Studies on the relationship between economic freedom and economic growth employ cross-country and panel data[2]. Even though most research shows that economic freedom and growth are highly correlated, the diversity of approaches produces different results and conclusions. Two main reasons explain the differences. First, studies use a wide array of econometric techniques and samples. Second, and more interesting for us, authors interpret results according to their own understanding of what economic freedom is.

In some of the studies in the growth literature, one variable not necessarily included in a summary index -the black market premium on foreign exchange, for instance-, is used as a proxy for economic freedom (e.g. Alesina, 1998 and Barro, 1991, 1997). Several analyses rely on one of the available economic freedom indexes as a good description of how free an economy is. Vega-Gordillo and Álvarez-Arce (2003) among others, employ the EFW overall index as an explanatory variable in regression models. A different approach is taken, for example, by Dawson (2003) and Carlsson and Lundstrom (2002), who examine which components of the EFW index have an impact on economic growth. Finally, Heckelman and Stroup (2000, 2002) or de Haan and Sturm (2000) prefer to elaborate their own index using data on all the components of the EFW index.

It is very difficult then to discern whether economic freedom enhances economic growth because it is not easy at all to identify economic freedom. In other words, economic freedom does not mean the same for researchers even if all of them use the EFW database. It can be the aggregated summary index -more or less sensitive to changes in the weighting scheme-, or it could be some of the components of that summary index, or even some measure obtained from the original data by using a data reduction technique (factor analysis, principal component analysis). In sum, the EFW concept of economic freedom has so many interrelated dimensions that efforts to squeeze it into simple indicators may lead us to wrong conclusions about institutional characteristics. And the ensuing ratings may result in a wrong ranking of the economic freedom of many countries which, in turn, may be a highly misleading indicator of what kind of countries

[2]See de Haan (2003) for a summary of empirical growth models with economic freedom.

we are dealing with.

3 Visualizing Economic Freedom.

In this section we do search for heterogeneity by analyzing the distributional structure of Economic Freedom data. We apply univariate kernel density estimation and resampling techniques such as permutations and boostraps tests to analyze null and confidence bands, respectively. We also rely on multivariate statistical methods, namely multivariate normal tests and multidimensional scaling, in an attempt to elucidate the statistical nature of the EFW dataset and produce a visual representation of the complex patterns governing the position of countries in the "economic freedom space".

3.1 Checking the distributional assumptions on Economic Freedom.

At a first step, we have estimated the probability density of the Economic Freedom Index using Gaussian kernel density estimation. Kernel density estimation provides a very effective way of examining the structure of data. Let $X_1, X_2, ..., X_n$ be a random sample of the Economic Freedom Index taken from a continuous and univariate density f. Given a kernel K and a positive number b, called the bandwidth, the kernel density estimator is

$$\hat{f}_n(x) = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{b}K\left(\frac{x - X_i}{b}\right),$$

where K is a function satisfying $\int K(x)dx = 1$. In this case, we have selected K_b to be the $N(0, b^2)$ density so that b plays the role of a scaling factor which determines the spread of the kernel. Assuming that f is Normal, we can compute the bandwidth b^* as

$$b^* = 1.06min(\hat{\sigma}, IQR/1.34)n^{-1/5},$$

where $\hat{\sigma}$ is the sample standard deviation and IQR is the interquartile range.

(Figure 1 about here: Kernel Density Estimation of the Economic Freedom)

The visual inspection of Figure 1 suggests that Economic Freedom does not perfectly fit an univariate normal distribution: the flat left tail and the mixture shape of the distribution, are two different traits that lead us to put into doubt the validness of the normality assumption[3]. The possible presence of a mixture component is a very interesting characteristic of the distribution, due to which we can think of several segments or clusters of countries with different behaviour with respect to economic freedom. That is, we may interpret the mixture nature of the Economic Freedom Index as a first sign of heterogeneity.

In order to confirm our first results about the probability distribution, we simulate the null band for the quantile-quantile plot of the best Box-Cox transformation to normality using permutations tests. Null bands show where the q-q plot is supposed to fall under the null assumption of normality. In Figure 2, we plot the null band for the q-q plot of the transformed variable with $\lambda = 1.2$.

(Figure 2 about here: Permutation Tests for the Economic Freedom)

Although the q-q plot does not fall on the right line of the theoretical quantiles for the normal distribution, overall, if we focus on the tails, it does fall within the null band. However, the null band at the tails is very irregular. It is interesting to note that when we use the Box-Cox transformation, we obtain a smoother distribution, closer to the normal assumption, that implies different quantiles. In other words, the number of countries within each segment changes as we transform the Economic Freedom distribution. Looking for further evidence, we construct a graphical bootstrap confidence band for the true density (see Figure 3). This confidence bands show an estimate of the variability of the density estimates. In Figure 3 we have plotted the band (shaded grey) that contains the true curve (black solid line) with some high probability. The tails of the distribution are sometimes outside the confidence band. Therefore, we reach the preliminary conclusion that normality is not a good assumption for Economic Freedom due to the existence of different clusters.

[3] We have tried with different kernel specifications such as Epanechnikov and cosine, and we come up with similar density estimations in all instances.

(Figure 3 about here: Bootstrapping Density Plots of the Economic Freedom)

In order to confirm all the previous results, we apply several omnibus tests[4] for the composite hypothesis of normality, and the result is surprising: according to these tests, Economic Freedom is normal! However, these statistical tests are incapable of capturing the presence of segments or clusters. We will be better able to unravel this paradoxical result only when we analyze the Economic Freedom Index as a multivariate variable.

3.2 The exploratory multivariate analysis.

The EFW Index is a multidimensional dataset of 38 different variables reduced first to 21 components and then to five major areas that, in turn, are aggregated into a single index. Aggregation means wasting information about heterogeneity, so we have studied the multivariate nature of the Economic Freedom Index looking at the five major components on one hand, and the 38 components on the other hand. As explained in section 2, the data set with 38 components presents a missing data problem -many survey data are not available for some countries-. To avoid this problem we impute the missing values[5]. We apply data augmentation techniques for generating the missing data, assuming they had been missed at random. We use the ***norm*** R package to get this goal. Then, we apply tests of multivariate normality, like the Shapiro-Wilk test, on the five aggregated areas and on the 38 desaggregated components[6]. We conclude that Economic Freedom is not multivariate normal and demands further analysis.

[4]More especifically, the Anderson-Darling test for the composite hypothesis, the Cramer-von Mises test, the Lilliefors (Kolmogorov-Smirnov) test and the Shapiro-Francia test, as performed by the ***nortest*** R package. Complete results are available from authors on request.

[5]Note that authors of the EFW index do somehow impute missing values, although implicitly, when they calculate ratings for the five major areas as averages of the available values.

[6]For the sake of space, imputation and tests results are not reported here, but they are available from authors upon request.

3.3 Multidimensional scaling.

Our claim is that a correct analysis of economic freedom, a latent variable with many indicators, requires multivariate treatment of the data. Multidimensional scaling (MDS) may be an illustrative first step in that direction. MDS is a way to produce a visual representation of complex patterns of (dis)similarities among a set of elements. It does so by exploiting the logical correspondence between the idea of dissimilarity and the mathematical concept of distance: two objects will be closer in an (euclidean) space the more similar they look according to some metric.

Let $x_i = (x_{i1}, ..., x_{i5})$ denote the vector representing the values that country i obtains in the five components of the Fraser Index. In other words, economic freedom of each country can be represented as a vector in the five-dimension space. Of course, five dimensions (not to speak of 38) are highly difficult for human mind to comprehend. That can be thought as one of the reasons for the Fraser Institute to squeeze all the information contained in the whole set of variables into a single summary index. MDS can help to reduce the dimensionality of the problem, making it possible to display on paper the configuration of objects (countries).

Suppose that the dissimilarity measure in economic freedom between countries i and j is given by $d_{i,j}$ which corresponds to the Euclidean distance between both countries in the five-dimension space $\delta_{i,j}$.

$$d_{i,j} = \delta_{i,j} = \sqrt{\textstyle\sum_{k=1}^{5}(x_{ik} - x_{jk})^2}$$

MDS builds a set of vectors in a l-dimensional space such that the matrix of euclidean distances among them ressembles as much as possible to the input matrix - the original matrix of distances in the five-dimension space -. The new coordinates in the distance function are estimated by minimising a badness of fit function. The most used function is stress. In this paper, we refer to Sammon´s non-linear mapping, which constructs a l-dimensional configuration that minimizes the following weighted stress

$$Stress = \frac{1}{\sum_{i \neq j} d_{ij}} \sqrt{\frac{\sum_{i \neq j} (d_{ij} - \widehat{\delta}_{ij})^2}{\sum_{i \neq j} (d_{ij})}}$$

where $\widehat{\delta}_{ij}$ is the euclidean distance between points i and j obtained from the estimated new configuration in the l-dimensional space.

Since our dissimilarity data were generated as distances in the five and 38-dimension spaces, the best possible configuration in two dimensions must be a distorted representation of the economic freedom attributes of countries. But it will likely be at least as good as the representation in $\Re^+$ given by the overall index because the stress must either go down or stay the same as the number of dimensions increases.

Results are presented graphically in figures 4 and 5. The most important thing to look for in MDS maps is clustering. That is, which point is close to which other points. When tight, clearly separated clusters are observed, each cluster should be treated as a different group. Larger distances tend to be more accurate because MDS tries to minimize the stress function that accentuates them. It must be noted that, for our purposes, a great advantage of Sammon´s non-linear mapping, compared to other forms of MDS, is that it puts much more emphasis on replicating small distances accurately. Element dimensions or attributes tend to put the elements (countries) in the map along an ordered continuum. But orientation of the picture does not matter, it is completely arbitrary. The ordering may go from north to south, from east to west or in any other direction. Any two vectors that point in the same direction are correlated, and the length of the vector from the origin to the country is an indicator of the variance of an attribute in explaining where points are on the map.

Although those countries with the most atypical behavior (Hong Kong and Myammar) are always in very extreme positions (the most free and the least free, respectively), the maps for the five areas and the thirty eight components look quite different. The 2-dimensional map for the five major areas is a visual representation highly concordant with the ranking of the Fraser Institute Index. Reading the map from the right to the left is very much like going down that ordered list. However, we cannot say the same about the map for the whole set of 38 variables. In this map we can observe how some points overlap, generating clusters composed of elements that do not correspond to countries that occupy adjacent positions in the Fraser ranking.

Even though the grouping of Australia (rank 7), Canada (8), Ireland (9), Luxembourg (10), New Zealand (3), Singapore (2), Switzerland (6) and United Kingdom (4) is coherent with their ranks, other visual clusters, like the one including Argentina (86), Dominican Rep. (54), Ghana (69) and Philippines (52), the one comprising Barbados (96), Colombia (107) and Morocco (84), or the one formed by Cameroon (98), Nepal (94), Papua New Guinea (95) and Venezuela (118) can not be easily detected in the EFW ranking. That is, the aggregation of the 38 components into a single index is somehow distorting the economic freedom picture because it masks much heterogeneity that, as we have seen, translates into a clustering arrangement. So, the ranking of countries according to economic freedom should be very different for some nations when we disaggregate the index. Our following aim will be to determine the ranking when we do not aggregate.

4 Hierarchical Ordered Partitioning And Collapsing Hybrid (HOPACH).

Although MDS methods provide an easy and useful way to visualize differences in economic freedom among countries, they suffer from several limitations. More specifically, they can neither rank nor group countries according to the degree of economic freedom. Some recent studies use multivariate techniques to overcome that drawback, trying to exploit all the information available in the EFW annual report. For instance, Heckelman and Stroup (2000) derive an empirically weighted index of growth-promoting economic freedom by using multivariate hedonic regression, and Caudill et al. (2000) apply factor analysis and principal component analisys in an attempt to derive a better picture of economic freedom. Even the Fraser Institute, in the 2001 version of the EFW report, used principal components analysis looking for a more objective weighting arrangement of the variables included in the index.

Here we rely on cluster analysis, namely on a hierarchical clustering algorithm called Hierarchical Ordered Partitioning And Collapsing Hybrid (HOPACH), originally developed by van der Laan and Pollard (2003) for clustering gene expression data. For our purposes, one of the main properties of HOPACH is that a final ordered list of items is obtained by running down the hierarchical tree completely. To be precise, HOPACH algorithm does not only create groups of homogeneous countries at all levels of detail. It also produces an economic freedom ranking.

4.1 HOPACH clustering algorithm.

HOPACH algorithm builds a hierarchical tree of clusters, starting at the root node and trying to find the right number of children for each parent cluster. It applies divisive (partitioning) and agglomerative (collapsing) steps iteratively, which allows mistakenly separated groups of elements to be brought back together. The clusters in each level of the tree are ordered according to the pairwise dissimilarities between cluster medoids. Consequently, the ordering of clusters and items within clusters is deterministic, which is one of the greatest advantages of applying this algorithm. Another improvement over traditional hierarchical methods is that splits are not restricted to be binary. In following subsections, each of the steps of the HOPACH procedure will be described in detail. But first we can summarize the algorithm as follows:

- Begin with all the items in the root cluster.
- Apply the partitioning method to the elements in the cluster.
- Order the resulting clusters.
- Collapse some clusters if necessary.
- Repeat the preceding steps in each level of the tree.

- Stop when each cluster contains no more than the minimum number of elements required by the partitioning method.

4.1.1 Partitioning and Selection Criterion.

HOPACH is a general clustering framework that could be applied with any partitioning method. In this paper we implement the Partitioning Around Medoids (PAM) procedure. PAM needs as input a dissimilarity matrix **D** based on any distance metric. If we are clustering n elements (countries) x_i, each a m-dimensional vector (m economic freedom components), let $d(x_i, x_j)$ denote the distance between elements i and j. PAM clustering procedure gives as result a set of medoids M^*. Clusters are identified by those medoids, which are elements of the root cluster. If K represents the number of clusters and $M = (M_1, ..., M_k)$ is any size K subset of the n elements x_i, it is possible to calculate the distance $d(x_i, M_k)$ of each element and each member of M. Let $min_{k=1,...,K} d(x_i, M_k) = d_1(x_i, M)$ and $min^{-1}_{k=1,...,K} d(x_i, M_k) = l_1(x_i, M)$ be the mininum and minimizer respectively. PAM chooses the medoids M^* such that $M^* = min^{-1}_M \sum_j d(x_i, M)$. Each medoid M^*_k corresponds to a cluster that includes the elements that are closer to this medoid than to any other. This clustering is captured by a vector of labels $l(X, M^*) = (l_1(x_1, M^*), ..., l_1(x_p, M^*))$

All partitioning methods require that the user specifies how many clusters to come up with. The question is how to select the correct number of child clusters for each parent cluster. There is no single right answer. Silhouette is frequently used as the criterion, specially since it can be calculated with any clustering algorithm and any distance metric. The silhouette for a given x_i element (country) is defined by the formula

$$S_i = \frac{b_i - a_i}{max(a_i, b_i)}$$

where a_i is the average dissimilarity of x_i with the other elements of its cluster, $b_i = min_l b_{il}$ and b_{il} is the average dissimilarity of x_i with the elements of cluster l to which it does not belong. When the similarity within the cluster of country x_i is maximum ($a_i = 0$), the silhouette is 1, its largest possible value. The opposite happens when the silhouette is -1. That is, the larger the silhouette, the better an element is matched to the other elements in its cluster relatively to how well it would match to elements in the next closest cluster.

It is standard practice to use the average silhouette over all elements of the parent cluster to select the number of child clusters k by maximizing average silhouette over the range of possible values for $k = 2, 3, ..., K$. If silhouette measures how well an element fits in its cluster, average silhouette assesses the strength of cluster membership overall. Average silhouette performs well as a measure of the global structure, but it is not able to detect finer structures, like the existence of relatively small clusters in the presence of some larger clusters or the existence of nested clusters within clusters. Pollard and van der Laan (2002a, 2002b) propose an alternative method called Mean (Median) Split Silhouette (MSS) which evaluates if further splitting would produce more homogenous groups.[7] The main point is to assess how well the elements in a cluster fit together by focusing in each cluster and running the clustering algorithm only to the elements in that cluster, disregarding the other groups.

In order to quantify MSS, take the k clusters and split each of them (by applying PAM and maximizing average silhouette). After the new split, each element defines a new silhouette, which is calculated relative to the elements with which it shares the parent. The average (median) of these silhouettes for each parent node is called the split silhouette SS_i, $i = 1, 2, ..., k$. If SS_i is low, elements in cluster i are homogeneous and that cluster should not have been partitioned. The Mean (Median) of all the split silhouettes over the k clusters is called MSS. HOPACH chooses the number of clusters k that minimizes MSS, producing on average the most homogeneous groups of elements.

In the first level of the tree it is not necessary to apply the partitioning method. In the economic freedom context, for instance, countries could be split into those which are above and those which are below the average value of the overall economic freedom index. Not partitioning a cluster ($k = 1$) is, of course, a possibility that could be selected

[7] Pollard and van der Laan (2002b) compare their method with four of the best performing direct methods in the literature, and MSS is better able to identify finer structures in several simulations.

if, for example, splitting results in a silhouette below a cut-off value. In our application, HOPACH does not partition any further if $min_k MSS(k) = MSS(1)$.

4.1.2 Ordering.

HOPACH is designed to order clusters in each level of the hierarchical tree. As a result of such a capacity, the algorithm produces a final ordered list of all the elements. In our case, the final order can be interpreted as a ranking of the countries based on their degree of economic freedom. However, some requirements must be met for that interpretation to be legitimate. HOPACH satisfies the required conditions to order clusters and elements in a sensible and significant way. The ordering procedure works as follows. We take a set of k child clusters whose medoids are $M_1, ..., M_k$. We define the distance between clusters as the distance between medoids, using the same distance metric that was applied in partitioning. Then HOPACH order the k children of a parent cluster left to right from largest to smallest distance to the cluster which is to the right of the parent in the preceding level. If the k child clusters are located in the right end of the tree level, the algorithm order them from smallest to largest distance to the cluster to the left of their parent.

Ordering clusters in the first level is slightly more difficult, because there are no parent clusters in a previous level that could be used to quantify distances. If there are only two clusters in the first level, the ordering does not matter[8]. The method suggested by van der Laan and Pollard (2003), is to apply the HOPACH algorithm to the medoids of the clusters in the first level, restricting the first partitioning to be binary. The clusters in the first level are ordered according to the unique final ordered list of the medoids. We apply a different method that is explained in section 4.2.

[8] Although it must be taken into account when interpreting the final ranking of the elements. If the cluster to the left includes those countries with less economic freedom, our final list will go from the most repressed economy to the most free country.

4.1.3 Collapsing.

Some clusters in a certain level of the tree can be very similar, regardless of which parent clusters they come from. If that is the case, collapsing might improve the clustering structure. HOPACH collapses until it can not improve the MSS for the whole level by collapsing any additional pair of clusters. Any fused cluster is assigned a new medoid, which can be chosen in several ways, like the closest element to the average of the two old medoids. With the purpose of preserving the tree structure, collapsing is performed by assigning the labels of one cluster to the other, using any criteria but in a consistent way. There is no collapsing at the first level of the HOPACH tree.

4.1.4 Labeling.

The path that each element takes when going down the tree is encoded by HOPACH in a label with one digit for each level in the tree. That digit identifies the child cluster containing the element (the number of child clusters for each parent is restricted to a maximum of 9). At each subsequent level, the label of each element is extended with another digit that represents the position of the child cluster to which it belongs. If HOPACH does not split a cluster, the labels of all its elements are extended with the digit 0 in that level of the tree. When the clusters in each partitioning step are assigned numbers from 1 to 9 sequentally from left to right, then the labels in the final level are numerically ordered to produce a ranking of the elements (countries). The whole path followed by an element can be reconstructed from its final label, and the cluster structure for level h of the tree can be pictured just by truncating final labels to h digits. For instance, a label 23415 at level 5 of the tree means that the element belongs to the fifth child of the first child of the fourth child of the third child of the second cluster from level 1.

4.2 Application of HOPACH to economic freedom.

As Pollard and van der Laan (2005) point out, although their method and R package were developed for clustering genes, they are also suitable for other frameworks with high-dimensional data structures. We apply the HOPACH algorithm, as implemented in the R package *hopach*, to clustering countries in an economic freedom data set: The 2004 Economic Freedom of the World. The *hopach* function is run as explained in the next paragraphs.[9]

In our application, HOPACH minimizes Median Split Silhouette in order (i) to optimize the number of children (restricted to a maximum of 9) for each parent, (ii) to decide whether to collapse or not any pair of clusters, and (iii) to identify the main clusters or determine the level of the tree below which cluster homogeneity does not improve any further. Below this level, HOPACH is run down without collapsing until getting the final ordered list. The maximum number of levels in the tree is restricted to 16 because of computational reasons.

We thought it appropriate to use Euclidean distance as the dissimilarity metric. Pollard and van der Laan (2005) recommend some distance based on correlation, like the cosine angle distance, for clustering genes. But our circumstances are different since we are not interested in clustering variables. We want to group countries based on similar levels of economic freedom. A much closer analogy to our goal is clustering individuals according to their gene expression vectors, and van der Laan and Pollard (2003) find that Euclidean distance is useful for that purpose.

The matrixes of euclidean distances between countries on the five and 38-dimension maps have been obtained without applying any weighting factors. Although a more sophisticated weighting scheme could be devised, it is not necessary for our goals. We are not interested in the problem of how to weigh each dimension of economic freedom, but in the necessity of considering all of them simultaneously. Since the Frasers summary

[9] Results do not significantly change when we use different options in the arguments of the *hopach* function.

index is obtained as a simple average of the five major areas, our results in the five-dimension space will be perfectly comparable to the original ranking. As we move into the 38 variables, we lose some direct comparability because their weights in the summary index are not exactly equal to each other.

With respect to collapsing, at each level HOPACH begins with the closest pair of clusters and proceeds sequentially, uniting pairs if and only if doing so reduces MSS. In order to choose a medoid for the new cluster after collapsing a pair of clusters, HOPACH maximizes medoid based silhouette

$$medsil = \frac{a - b}{max(a, b)}$$

where a is distance to medoid and b is distance to next closest medoid.

Finally, ordering steps are implemented in the following way. In the initial level of the tree, clusters are ordered by maximizing the empirical correlation between distance apart in the ordering and inter-medoid distance. Elements within clusters are ordered at any level attending to the distance with leftmost medoid.

5 Results

In this section we comment on the results - both clusters and ordered lists - produced by HOPACH. When applied to the five major areas data, HOPACH groups the 123 countries in two main clusters in the first-level partitioning, with $MSS(2) = 0.2662473$. Then the algorithm runs down, until producing the final ordered list of elements in level 9. HOPACH proves to be able to detect subtler structures in its application to the richer dataset composed of the 38 variables underlying the overall index. In this case, the degree of heterogeneity captured by the grouping is higher, since the optimal clustering happens in level 3, where HOPACH discovers 15 main clusters, with $MSS(15) = 0.04862522$. Also here, as in the preceding case, the algorithm requires 9 levels to obtain the final ranking of countries.

To facilitate the evaluation of the final lists resulting from the clustering algorithm, we compare them with the Fraser Institute's original ranking. The three ranked lists are shown in Table 1. The correlation matrix for the three rankings is given in Table 2. Correlations between the three of them are high, all above 0.79. These high scores do not imply that the ranks for individual countries do not change. Nevertheless, it is worthy of note that Hong Kong keeps the first position in the three ordered lists, with Singapore in 2nd or 3rd place, whereas Congo Democratic Republic, Zimbabwe and Myanmar consistently occupy the last three positions.

(Table 1 about here: Economic Freedom Rankings)

(Table 2 about here: Correlations)

The highest correlation coefficient is 0.89 between the first ranking (R1), based on the Fraser Index, and the second one (R2), derived from the application of the HOPACH algorithm to the five major areas of the EFW Index. A comparison of the ranks provided by R1 and R2 brings in some interesting results. On average, each country's ranks in R1 and R2 differ by 12 places (the median change is a 10-place movement). The biggest change from R1 to R2 is China's jump, which gains 66 positions and gets the 25th place. On the other hand, Sri Lanka is the most significant drop in the list, with a lost of 36 spots.

The first 16 countries in R1 are assigned the first 16 places in R2. Estonia, which tumbles from the top 16 economies, falling 28 positions from its original ranking to 41th, is the only exception. Germany takes its position in the leading group, making it the world's 15^{th} freest country. Leaving aside both economies, Canada is the country whose rank suffers the greatest change (a four-position improvement) among the top 16. At the botom of the list, as mentioned before, we find Congo Democratic Republic, Zimbawe and Myanmar, in both R1 and R2.

The dramatic changes of the posititions of some countries with intermediate ranks in R1 are not surprising. The difference in the Fraser summary index between United Arab Emirates, ranked 17^{th} with 7.5 points out of 10, and Central African Republic, ranked

120^{th} with 4.5, means that more than 100 countries are clustered in a 3-point range. The way of constructing the summary index makes economies to look very much like each other. By taking simple averages of all the variables, the EFW index suppresses much of the heterogeneity among countries. HOPACH allows to retrieve a great deal of that information and, consequently, generates new ranks for many countries in R2. For example, two of the new EU members, Malta and Lithuania, obtain the same rating (6.8) in the Fraser summary index, and they occupy ranks 47 and 48 respectively. But they differ in their economic freedom features. Malta is represented in the five-major-area space by the vector (5.8, 7.0, 7.1, 7.0, 7.0), whereas Lithuania´s coordinates are (5.5, 5.3, 9.4, 7.8, 5.8). HOPACH captures that heterogeneity, and puts Lithuania in the 28^{th} position and Malta in the 57^{th}. Only those countries that stand out because of their very high or very low degree of economic freedom tend to maintain their original positions.

Changes from R1 to R3 are much more acute, although the correlation coefficient between both rankings is high, almost 0.82. In this case, the country that observes the biggest movement in its position is Uganda, which drops 60 spots to number 116. On average, going from R1 to R3 implies that each country moves up or down the list by 16 places (the median change is a 12-place movement). Such great movements are logical since R3 has been obtained from the application of the clustering algorithm to the 38 variables incorporated into the summary index. In that way, R3 takes into consideration more heterogeneity than R1 or R2. The two countries of our example, Malta and Lithuania, share the same rating only in five variables. For some of the other 33 variables, we find differences as large as 5, 7 and even 10 points.

6 Concluding remarks.

This paper has investigated the issue of whether indexes of economic freedom can be used as a reliable grading scale to group and rank countries along a continuum from most free to least free. The responsibles for the publication of such indexes recognize that economic freedom is complex and multidimensional. Summary indexes, like those of the Fraser Institute and the Heritage Foundation, try to simplify that complexity. Once all the relevant underlying components have been rated, the aggregate measure of economic freedom for each country is obtained by taking the simple average of its ratings. The resulting value of the summary index is the basis for the ranking of the country. This kind of information is of fundamental importance since it is viewed as a relative quality measure of the institutional context of an economy.

We suspect that rankings based on averages can be highly misleading, especially for some countries, because they abstract away from simultaneous sources of heterogeneity. Simple average tends to smooth out significant differences across countries in economic freedom components. As Gwartney and Lawson (2003) themselves conclude, small differences in the summary index between countries should not be taken very seriously. They even provide some illustrative information for the 1998 - 1999 time period.

> *The summary ratings range from Hong Kong's 8.88 to Myanmar's 3.33 and most of the ratings are clustered in the middle. There are 25 countries in the 7.0 to 7.99 range, 40 with ratings between 6.0 and 6.99, and another 30 with ratings between 5.0 and 5.99. Thus, 95 of the 123 countries have ratings in the range between 5.0 and 8.0. There are only 10 countries with summary ratings above 8.0 and only 18 with ratings below 5.0. Because of this clustering, a small difference in rating (for example 0.5) among two countries in the middle range sometimes generates ranking differences of 15 or even 20 positions. Thus, the ranking differences, particularly for countries in the middle, sometimes suggest that the differences in economic freedom are larger than is really the case.*[10]

Our findings about the statistical nature of both the overall index and the whole EFW dataset, as well as the maps resulting from the MDS analysis, help crystallize our suspicions that usual ratings may lead us to wrong conclusions. The multidimensional

[10] Gwartney and Lawson (2003), p. 418

framework defined by economic freedom requires a multivariate treatment of the data set. We have presented a study that uses a novel methodology, called HOPACH, which was developed by van der Laan and Pollard (2003) in a different setting. This new clustering methodology we have incorporated into the study of economic freedom produces both a segmentation and, more novelly, an ordered list of elements. We have applied HOPACH to the Economic Freedom of the World data set. The HOPACH package has been implemented in a way that allows to rank countries according to the differences among them in terms of the components of the index published by the Fraser Institute. Our results support the hypothesis that a more sophisticated treatment of the same data set substantially changes the rankings of several nations.

This paper does not answer the question of how to aggregate freedom measures into a summary index. Our aim was to get a classification of economic freedom through a procedure that makes use of all the information provided by the economic freedom components and by the differences among countries. Of course, HOPACH clustering algorithm does not offer a definitive answer to the question this study deals with. In fact, it is not the only reasonable method for our purposes. Nonetheless, it appears a suitable way to take into account the several factors that simultaneously impinge on economic freedom.

One further point is worth making about how to interpret our results. Any multidimensional dataset is likely to reflect the effects of some unsuspected source of differences and, to a lesser or greater extent, any multivariate method will reveal them. In fact, that is exactly the case with our study, which applies a multivariate clustering method to the treatment of the 2004 Economic Freedom of the World dataset. The ranked lists, as well as the heterogeneity among countries and the homogeneity within clusters, should be translated into terms of economic freedom only as long as the observed variables are accurately depicting the features of that unobservable concept and nothing else.

To conclude: Many theoretical and empirical investigations on economic freedom make no effort to discern the various components of the available indexes. In that sense, rankings and conclusions based on values of the overall index should be taken with caution since ad-hoc aggregation may hide valuable evidence. Having a closer look at the ways in which countries differ seems worthwhile precisely because of their normative implications for future policies and institutional reforms. The EFW and similar indexes offer a huge amount of information that should not be wasted by paying all the attention only to overall measures of economic freedom.

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Table 1: Rankings

Country	**Code**	**R1**	**R2**	**R3**
Albania	ALB	93	86	111
Algeria	DZA	119	104	70
Argentina	ARG	86	115	53
Australia	AUS	7	8	21
Austria	AUT	16	16	16
Bahamas	BHS	72	91	118
Bahrain	BHR	34	43	41
Bangladesh	BGD	85	114	91
Barbados	BRB	96	90	105
Belgium	BEL	20	18	28
Belize	BLZ	68	55	112
Benin	BEN	103	84	100
Bolivia	BOL	58	79	80
Botswana	BWA	19	33	43
Brazil	BRA	77	69	76
Bulgaria	BGR	79	66	63
Burundi	BDI	116	92	120
Cameroon	CMR	98	94	101
Canada	CAN	8	4	26
Central Afr. Rep.	CAF	120	105	99
Congo, Dem. R.	COD	121	121	122
Chad	TCD	106	108	92
Chile	CHL	25	39	5
China	CHN	91	25	78
Colombia	COL	107	100	65
continued				

Country	Code	R1	R2	R3
Costa Rica	CRI	31	42	35
Cote d'Ivoire	CIV	87	113	98
Congo, Rep. Of	COG	115	103	94
Croatia	HRV	83	65	72
Cyprus	CYP	53	54	24
Czech Rep.	CZE	42	36	22
Denmark	DNK	15	14	12
Dominican Rep.	DOM	54	75	89
Ecuador	ECU	97	118	83
Egypt	EGY	76	74	61
Estonia	EST	13	41	4
Fiji	FJI	78	88	110
Finland	FIN	11	13	11
France	FRA	45	23	37
Gabon	GAB	112	93	96
Germany	DEU	22	15	14
Ghana	GHA	69	67	56
Greece	GRC	43	29	7
Guatemala	GTM	63	82	82
Guinea-Bissau	GNB	117	102	104
Guyana	GUY	65	26	46
Haiti	HTI	82	110	97
Honduras	HND	61	78	55
Hong Kong	HKG	1	1	1
Hungary	HUN	26	38	32
Iceland	ISL	14	10	29
India	IND	70	70	106
continued				

Country	**Code**	**R1**	**R2**	**R3**
Indonesia	IDN	88	71	86
Iran	IRN	81	73	87
Ireland	IRL	9	9	20
Israel	ISR	51	22	13
Italy	ITA	39	20	17
Jamaica	JAM	41	48	50
Japan	JPN	40	32	34
Jordan	JOR	38	35	47
Kenya	KEN	62	77	117
Kuwait	KWT	21	31	40
Latvia	LVA	36	37	6
Lithuania	LTU	48	28	31
Luxembourg	LUX	10	11	9
Madagascar	MDG	102	112	68
Malawi	MWI	100	98	108
Malaysia	MYS	60	59	59
Mali	MLI	99	96	71
Malta	MLT	47	57	44
Mauritius	MUS	28	46	49
Mexico	MEX	59	72	66
Morocco	MAR	84	87	75
Myanmar	MMR	123	123	121
Namibia	NAM	64	60	45
Nepal	NPL	94	85	109
Netherlands	NLD	12	12	19
Pap. New Guinea	PNG	95	106	95
New Zealand	NZL	3	6	8
continued				

Country	**Code**	**R1**	**R2**	**R3**
Nicaragua	NIC	67	80	115
Niger	NER	108	101	102
Nigeria	NGA	90	107	90
Norway	NOR	37	21	15
Oman	OMN	18	30	42
Pakistan	PAK	92	111	67
Panama	PAN	30	51	38
Paraguay	PRY	75	81	81
Peru	PER	46	50	79
Philippines	PHL	52	76	54
Poland	POL	66	63	73
Portugal	PRT	29	19	18
Romania	ROU	104	95	77
Russia	RUS	114	120	85
Rwanda	RWA	110	109	93
El Salvador	SLV	27	53	33
Senegal	SEN	89	68	69
Sierra Leone	SLE	111	83	119
Singapore	SGP	2	2	3
Slovak Rep	SVK	55	64	23
Slovenia	SVN	74	24	30
South Africa	ZAF	49	61	57
South Korea	KOR	33	45	62
Spain	ESP	32	34	36
Sri Lanka	LKA	80	116	88
Sweden	SWE	23	17	10
Switzerland	CHE	6	5	2
continued				

Country	**Code**	**R1**	**R2**	**R3**
Syria	SYR	105	89	114
Taiwan	TWN	24	40	60
Tanzania	TZA	73	27	107
Thailand	THA	50	58	58
Togo	TGO	113	99	103
Trinidad Tob.	TTO	35	49	48
Tunisia	TUN	71	56	74
Turkey	TUR	101	119	84
Uganda	UGA	56	52	116
United Kingdom	GBR	4	7	25
Ukraine	UKR	109	97	113
Unit. Arab Em.	ARE	17	44	51
Uruguay	URY	44	47	39
United States	USA	5	3	27
Venezuela	VEN	118	117	64
Zambia	ZMB	57	62	52
Zimbabwe	ZWE	122	122	123

Table 1: Rankings

Table 2: Rankings correlations

CORRELATIONS	R1	R2	R3
R1	1.0000	0.8924	0.8194
R2	0.8924	1.0000	0.7978
R3	0.8194	0.7978	1.0000

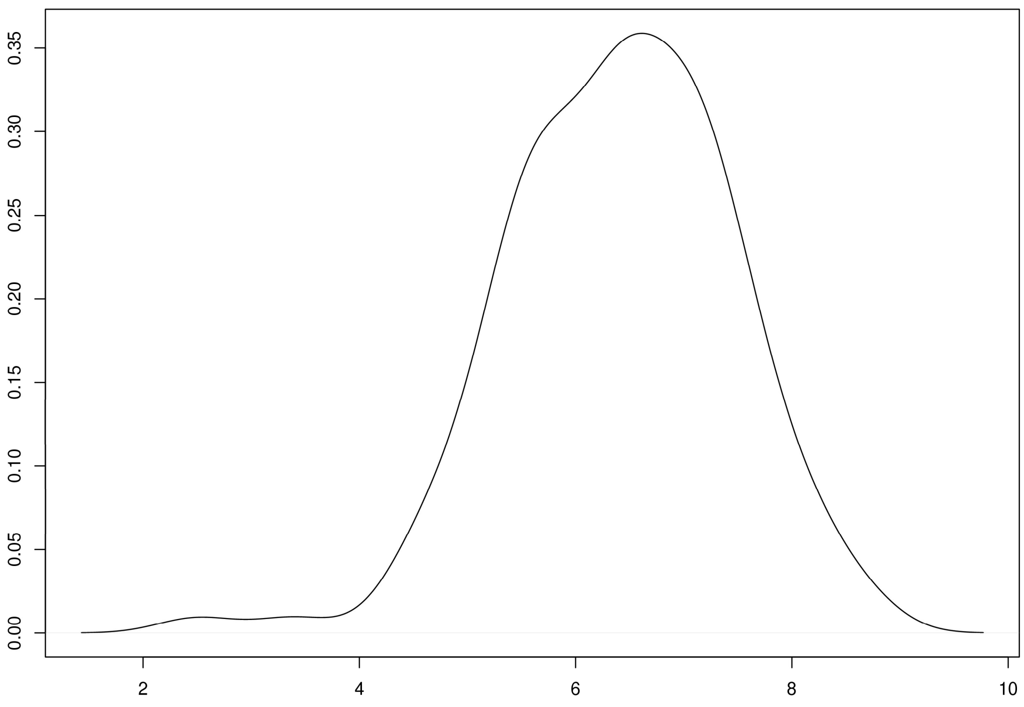

Figure 1: Kernel Density Estimation of the Economic Freedom

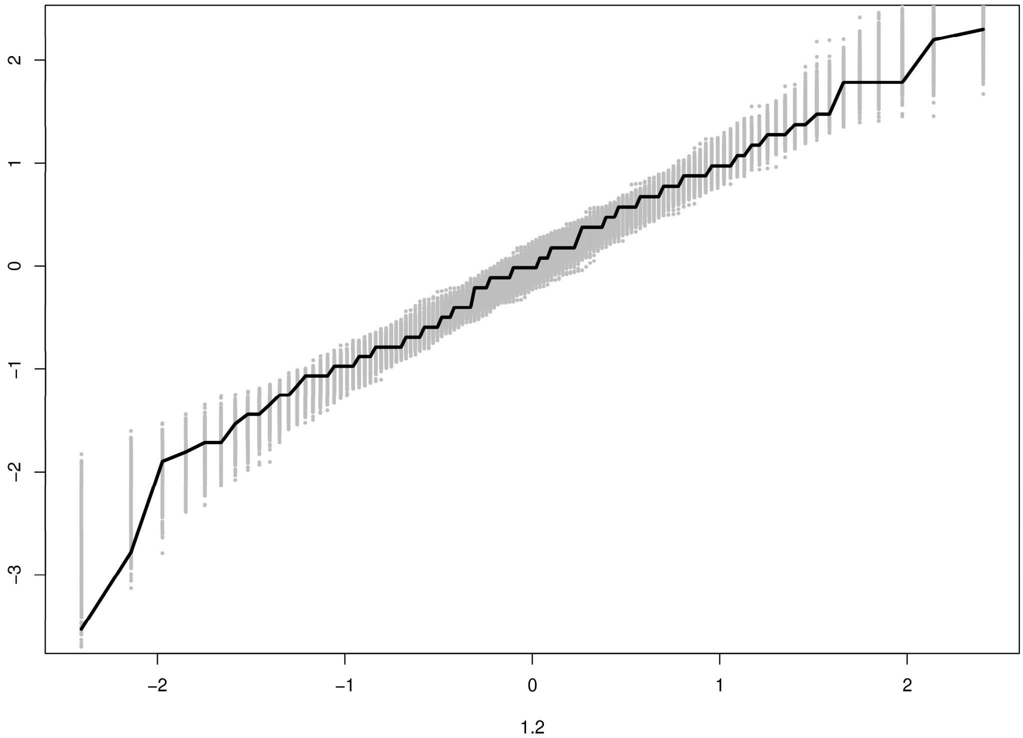

Figure 2: The Null Band for the Quantile-Quantile Plot

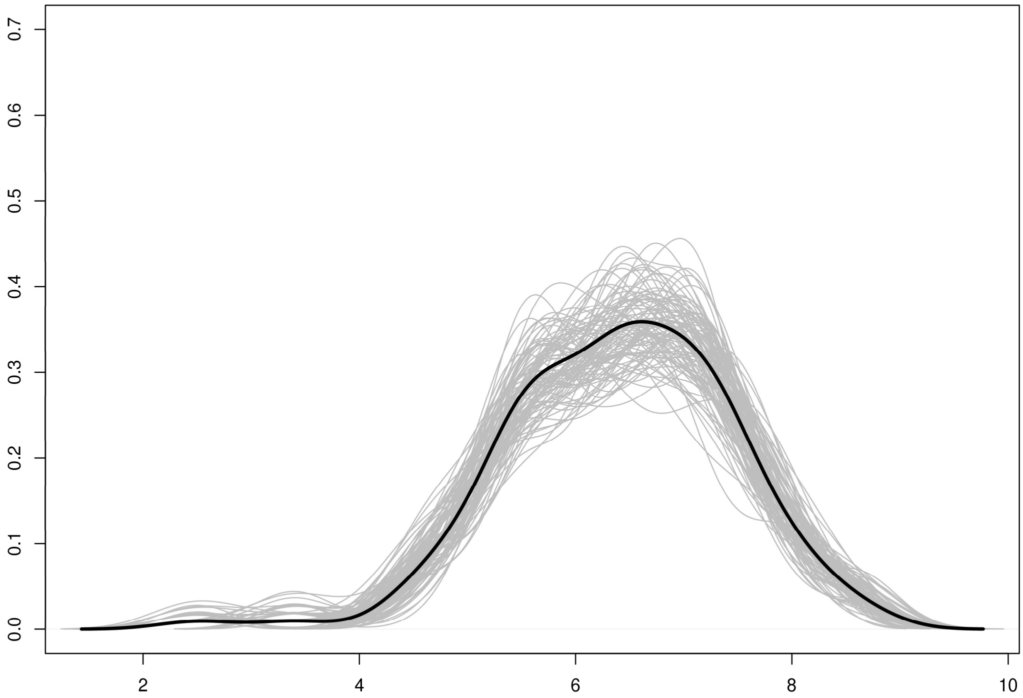

Figure 3: The Bootstrap Confidence Band for the True Density

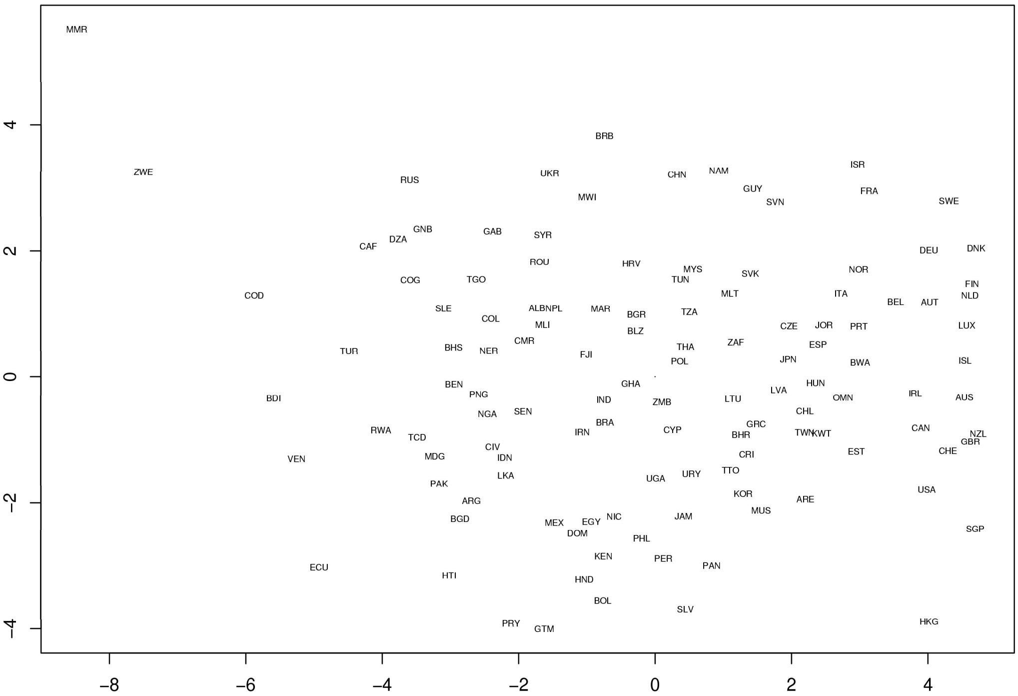

Figure 4: Multidimensional Scaling Representation of the Five Components

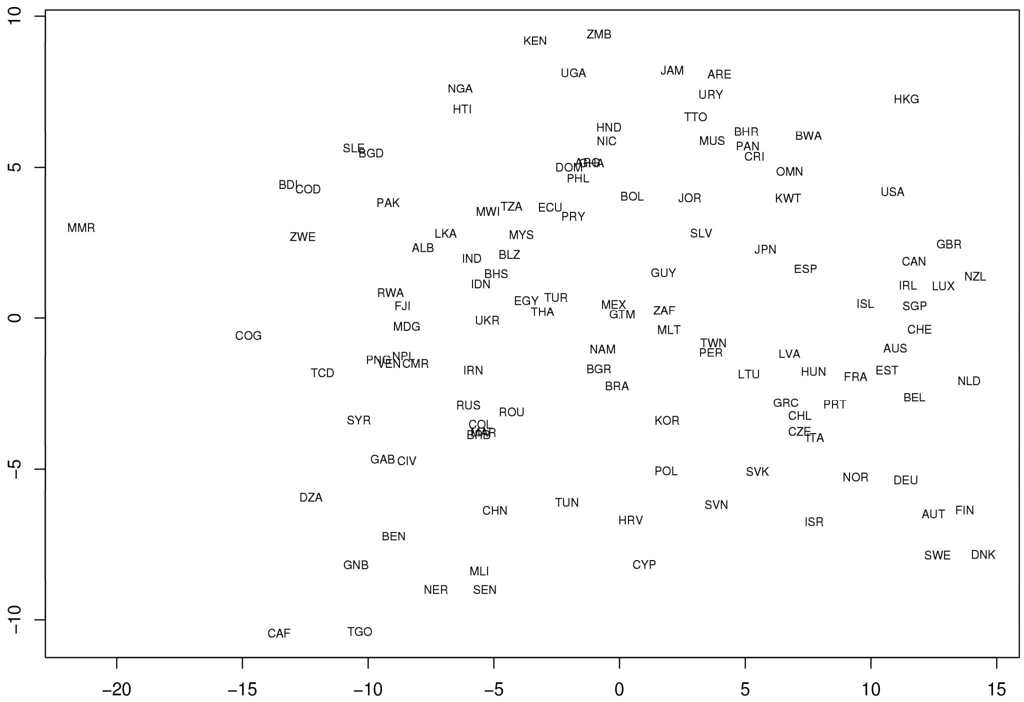

Figure 5: Multidimensional Scaling Representation of the Thirty Eight Components