Wealth, Urbanization and Infrastructure: Structuring the Countries of the World

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Abstract

Countries around the world are very diverse, not only on geographical, political and cultural ground, but as well in means of economic development. Detecting latter differences and their sources has long been the aim of development economics. Since a country-by-country assessment is often infeasible due to the large number of countries existing, classification is a necessary tool to group countries with similar patterns and cater adequate support to each one of these groups.

A very simple, yet widely used classification is that into *least developed*, *less developed* and *developed countries*, which is predominantly based on GDP per capita values. The analysis of this paper wants to depart from this simple classification and tries to classify the countries of the world in a more subtle way by including variables describing economic well-being, as well as variables accounting for economic growth, hence giving development perspectives for the resulting groups. The focus is restricted to the categories *wealth*, *urbanization* and *infrastructure*, explaining economic growth to a large extent.

The methodology used to classify the countries is the statistical device *cluster analysis*.

The results of the analysis provide the basis for a new way of clustering the countries of the world according to the focus of the paper. The existing division into *least developed*, *less developed* and *developed countries* cannot be supported by this analysis and interesting features of individual OECD and EU economies, as well as EU accession candidates are revealed.

Key Words: Economic Development, Wealth, Urbanization, Infrastructure, Cluster Analysis, Factor Analysis

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Contents

List of Figures

List of Tables

1 Introduction

The heterogeneity of living conditions across countries of the world has motivated experts from various disciplines - sociology, geography, economics and many others - to look for specific measures and variables to categorize and classify the countries and find similar structures among sub-groups of the overall entity.
Comparability and objectiveness of the variables and measures used are prerequisits for each individual approach, yet they are, at the same time, one source of differentiation between the various ways of classification. The specific focus of the respective approach and the connected questions that shall be answered by the results of the research are the key parameters of differentiation underlying each classification procedure.
Living conditions can be measured in a variety of ways. Wealth, i. e. monetary well-being, is a widely used indicator of living conditions and often measured in some form of GDP[2] per capita.[3] Nevertheless, a wide range of other indicators describing living conditions exists, including the provision of goods and services of basic needs or geographical aspects such as climatical conditions.
A key task and desire for both, further developed countries and international organizations, is to enhance economic development in less developed countries in order to reduce the gap of living conditions between wealthier and poorer countries in the world. Good results towards this goal could theoretically be achieved through a country-by-country assessment and tailoring trade structure and development support for each individual country. In practice, this would however be infeasible due to the large number of bilateral and multilateral agreements that would be needed in such a scenario and the diversity of emphases that would be expressed.
Therefore, it has long been the aim and practice to classify countries according to meaningful variables and indicators to obtain the utmost similarity among members of a designed group, and cater appropriate development support to them.
One way of forming sub-groups among the countries is to do so on behalf of geographical aspects, as mentioned above. Thus, groups commonly used by the United Nations, the World Bank and other international institutions are *South-East Asian Countries*, *African Countries*, or if a more subtle description is needed, *Sub-Saharan African Countries*, and so forth. Even though these geographical groups roughly combine countries with similar economic

[2]A list of Abbreviations used throughout the paper is provided in Appendix A.

[3]A more detailed discussion on different types of per capita measurements of GDP - will it be nominal, purchasing power parity or others - will follow in the upcoming chapters.

conditions, large heterogeneity among these countries is still present due to the fact that economic and economically influential variables are not the ones underlying this form of classification.
The most commonly utilized form of classification of countries is the one dividing the countries roughly into developing and developed countries, with GNI per capita,[4] i.e. a purely monetary variable as the main parameter underlying the classification. This classification is used by the most prominent agencies, the World Bank, the International Monetary Fund and the United Nations. Among this rough division, a further sub-division is performed into *low income countries*, *lower middle-income countries*, *upper middle-income countries* and *high income countries*.[5] The World Bank bases parts of its lending conditions on this sub-division of its member countries.
The UN performs a sub-division into *less developed countries* and *least developed countries* among the developing countries. Countries belonging to the group of *least developed countries* receive special development aid and treatment. This classification is also relevant in the WTO framework. LLDCs are subject to so-called *special and differential treatment* in various trade related aspects.(Diaz-Bonilla, Robinson & Thomas (2002))
Another way of assessing a comparison of living conditions in different countries is the Human Development Indicator proposed by the UN. It takes into account a variety of variables, both economic and non-economic, and gives each individual country a single value based on an index.

As introduced, there exists a variety of different approaches to classify the countries according to their respective stages of development. However, some shortcomings are imminent to them as grouping of countries is always connected to a loss of individual information and thus new sub-groups only give information about certain variables taken into consideration.
The criticism, on which this paper is based, is that the division of the countries into *least developed*, *less developed* and *developed countries* is too rough and does not take into account that the countries within each group are very heterogeneous and on different stages of development. As a consequence, a more subtle classification, with groups of countries that are more homogeneous among themselves as an outcome, can be helpful to allow for more specific treatment of certain countries and to set forth different sources of underdevelopment.

[4] The change from GNP to GNI was a merely notational change from the SNA 1968 to the SNA 1993, with $GDP = GNI + Net\ factor\ payments$. Further details are available on http://www.worldbank.org/data/changeinterm.html

[5] A survey of this classification is given on http://www.worldbank.org/data/databytopic/classgroups.htm.

Throughout this paper, I want to perform a more detailed analysis of the stages of development of the countries in the world with the aim of classifying the countries into relatively more homogeneous groups or clusters. The focus of this work is the analysis from a *wealth*, *urbanization* and *infrastructure* perspective. Variables measuring these indicators are developed and included since they are, on the one hand, the key components driving economic development as will be revealed in Chapter 2, and on the other hand, subject to objective quantification. Latter aspect is an important feature since there exist several approaches to classify countries including variables of "openness to trade" or "political stability",[6] which are, by nature, difficult to quantify objectively with interpretable numerical outcomes.
The methodology used in this paper to classify the countries into groups with similar characteristics is the statistical device *cluster analysis*. A detailed description of this methodology follows in Chapter 4. After performing the cluster analysis to the group of countries, a *factor analysis* is following to identify the key factors that account for the distinctiveness of countries in terms of development.
The result of the joint analysis should give a suggestion, how to classify the countries of the world reasonably in terms of their development stages to allow for a more specific treatment than what is possible under the current classification into *least developed*, *less developed* and *developed countries* and possibly detect interesting patterns as well among those countries considered being *more developed*.

2 Motivation for the Specific Analysis

The aim of this paper has been given as classifying the countries of the world into more homogeneous groups according to development indicators. Thus, a motivation for the specific variables to be included into the analysis has to be given, as well as the motivation underlying the choice of the specific statistical device to perform the analysis.

[6] A treatment of a variable called "institutions" is for example used in Açemoglu, Johnson & Robinson (2001).

2.1 Variables of Interest

Different variables of influence are needed as the basis for the analysis. However, the research of this paper should be restricted to the use of objectively quantifiable variables and not on constructed, scaled variables with a subjective connotation.

Even though most constructed indicators are based on scientific grounds, a subjective note is always adherent to them and subject to discussion. *Political stability*, for example, is apart from objective comparability across countries always a matter of perception. *Hard figures* like *km*s of road per area or the population density of a country will always resist criticism easier.

Wealth, as measured in some form of income per capita, is the best comparable and most appropriate variable to measure well-being of individuals and thus used most frequently as an indicator for development. A certain level of wealth is achieved over time through economic growth. Economic growth can either be modelled in an exogenous way, as in the basic Solow-Growth-Model Solow (1957)

$$Y_t \ = \ A_t \ K_t^{\alpha} \ L_t^{1-\alpha} \tag{1}$$

with Y_t being output in time t, K_t being the capital stock in time t, L_t being the labor input in time t and α indicating the capital share of the factor payments. A_t determines the so-called total factor productivity, which is given exogenously in this model.

Or economic growth can be modelled endogenously, as in the basic model proposed by Romer (1990)

$$Y_t \ = \ K_t^{\alpha} \ (A_t \ L_{Y,t})^{1-\alpha} \tag{2}$$

with $L_{Y,t}$ the share of labor in production, the other variables defined as above and A_t evolving over time as

$$\frac{dA_t}{dt} \ = \ \eta \ A_t^{\phi} \ L_{A,t}^{\lambda} \tag{3}$$

with $\eta > 0$, $0 \leq \phi \leq 1$ and $0 \leq \lambda \leq 1$ and $L_{A,t}$ being the share of labor in R&D. Thus, this model takes total factor productivity as endogenous.

For the purpose of this paper it is not necessary to go further into details of growth theory.[7] But it is important to know what drives the TFP, in order to identify the roots of economic growth and as a result the level of GDP per capita, i.e. our definition of wealth.

At this point, the new approach of this paper as opposed to the common approach to classify the countries merely according to their level of GDP per capita should become apparent. There are various variables of influence accounting for economic growth and thus for well-being. But not all of these variables have to take specific values in order for a country to be at a certain level of development. In fact, countries at similar stages of development can have very different values of the variables of interest. Consequentially, they need support to improve the level of those variables with relatively lower values.

The clear focus should be on variables that account for economic growth. Hence, higher values for these variables indicate good perspectives of development for the respective countries and less requirement for development support in comparison to those countries with relatively lower variable values.

The approach of this paper will focus on *wealth* as an indicator for well-being, but will add variables that account for and enhance economic well-being to classify the countries. These variables are restricted to the categories *urbanization* and *infrastructure* because these are objectively quantifiable and explain wealth as measured in GDP per capita to a large extent. Moreover, this restriction has to be made to set limits to the research of this paper.

The literature offers further suggestions of variables to explain economic wealth. Açemoglu, Johnson & Robinson (2001) include the variable "institutions" describing institutional stability and Edwards (1997) tests various suggested indicators of openness to trade. However, these indicators share the common drawback that they are not based on clear and objective numerical measures, but on created indicators. That is the reason why the analysis of this paper does not consider these variables. Moreover, this analysis does not include variables describing the geographic location of a country, which is done by Gallup, Sachs & Mellinger (1998) and other authors, because there exists no clear numerical classification and an inclusion of such variables

[7] Modern growth theory often divides the equations above by L_t to directly consider per capita values. In-depth coverage of growth theory can be found in numerous advanced textbooks. However, this short introduction should set forth the key question underlying the variables included into the analysis of this paper: What variables drive economic growth?

would tilt the results of this paper towards grouping countries of common geographic regions together, a classification this paper wants to depart from.

2.1.1 GDP per capita measuring Wealth

The first variable the analysis of this paper takes into account is wealth as measured in GDP per capita in terms of purchasing power parity, since this enhances greatest comparability among countries, even though the limitations of PPP comparisons have long been subject to discussions.[8]

2.1.2 Variables of Demographic Distribution

The next group of variables included in the research of this paper are those measuring different types of demographic distribution within the countries.
One important relationship found in the literature is a positive correlation between the degree of urbanization and economic growth. Nevertheless, one should be aware of the fact that too little concentration provides chances for further spillover effects and positive externalities, whereas too high concentration can lead to congestion and higher social costs. However, the correlation is positive throughout a whole cross-country sample, giving reasons to include the variable *urbanization*. A detailed discussion on the relationship between urbanization and economic growth can be found in Henderson (2000).
The same author proposes another variable of interest called *primacy*, as the share of the population of one country living in the largest city or metropolitan area. In many developing countries the presence of one large major city is evident, which can serve as a booming center, but also block further development when social costs - like housing prices or environmental damage - outweigh the benefits. A cross-country study again revealed a positive correlation with economic growth.
A third, straightforward demographic variable to be included is *population density* of a country, to measure the overall demographic structure of a country, even though Gallup, Sachs & Mellinger (1998) could not find a significant correlation between population density and economic growth in their work. However, growth theory argues that population density coincides with the

[8] A more detailed explanation on what data is being used and what caveats hold will follow in the next subsection.

provision of public goods, like hospitals, schools, etc., and thus enhances economic development.
In preparatory computations I included absolute variables, like the absolute size of the population in one country or the population in the largest city, but it turned out that the use of relative variables made more sense for comparative purposes of the analysis.

2.1.3 Infrastructure Variables

The remaining five variables included in the analysis of this paper are related to infrastructure, even though the variable *landlocked* appears to be a purely geographical one.
It is a given that transportation costs distort perfect market outcomes, thereby diminish possibilities for economic well-being. An easy model of the impact of transportation costs is given in Obstfeld & Rogoff (1996), pp 249-258. Infrastructure investments decrease these transportation costs. Consequentially, it is reasonable to include variables determining infrastructure.
A widely used variable is the ratio *roads per area*[9] (Nosal & Rupert (2002) and others) as measuring the infrastructure for transportation of tangible goods.[10]
Roads do often not equal *roads* across countries, even though it is assumed that all can be used in some way by cars and trucks. One way to assess the quality of the roads is to include the variable *paved roads* giving the percentage value of the overall roads that are paved as done by Canning & Pedroni (1999).
Phone lines per capita decrease the transportation costs of information being a useful device to measure infrastructure. This variable is, thus, often included and should also underly the analysis of this paper.
Another variable proposed to measure infrastructure is the *amount of kilowatts of electricity produced per person* (Canning & Pedroni (1999)). This indicator helps to measure the fueling of the productive sector. As an alternative, the *electricity consumption per capita* could be considered, but it is more correlated with household income and puts less stress on the specific country's endowment with natural resources.

[9] This is measured in km of road per km^2 of area. Details will follow in the next section.
[10] It would not be possible to replace this variable by *railroads per area* the presence of railroad systems is much less evenly distributed on the globe with numerous countries not having one at all.

As mentioned above, the last included variable, *landlocked*, differs from those presented before. First, it can be understood as a geographical variable, but in this context it should merely serve as an infrastructural variable indicating a country's accession to maritime transportation, an important form of transportation of voluminous goods. Further, this variable is the only non-continuous, but binary variable utilized in this analysis. However, considering the importance of this form of transportation as an infrastructural advantage, it will be included into the analysis.

Nosal & Rupert (2002) propose financial stability to be part of the infrastructure, yet I decided not to include it due to difficulties in measuring this variable. Again, the analysis of this paper relies on measures of *physical infrastructure* rather than *political* or *social* infrastructure with the obvious consequences restricting the policy implications from the results of this paper to the categories implemented into the analysis.

These nine variables included into the analysis cover a wide range of differentiations between countries and should mirror differences in the categories of interest - *wealth*, *urbanization* and *infrastructure* - in a detailed and extensive way. Other categories often employed to discuss differences among countries are those of *political institutions*, *geography* and *education*. Repeatedly, it has to be said that these categories can only be measured less objectively and are not in line with the focus of this paper.

2.2 The Method Utilized in the Analysis

Given the goal of this paper to classify the countries of the world according to specific variables of interest, the statistical task has to encompass a reduction in dimensionality, since the outcome will not characterize each observation, i.e. country, by its values of the respective variables, but by its belonging to one certain group. The initial situation for the underlying country data gives values for each variable and country but does not give any hint for an already occurred grouping. Hence, the question is, whether some "natural groups" of countries with similar characteristics are hidden behind the data set.
The statistical methodology that fulfills exactly this task to identify groups - or *clusters* - within a given data set without prior specification on the data or prespecified groups, is *cluster analysis*. Therefore, this methodology will be used for this analysis and is presented in detail in Chapter 4.

After performing a clustering of the countries, it could be of interest to detect the variables or combination of variables that are mainly responsible for the sub-division of the countries, i.e. the combinations of variables that contributed extensively to the specific outcome of the *cluster analysis*. This task is, as well, tackled by dimension reduction. One way of achieving this is to detect the *principal components* of the data set using the *principal component analysis*. Another way is to determine the key *factors*[11] that are correlated the most with the data matrix. This is done by the so-called *factor analysis*. For the purpose of this paper, I decided to perform a *factor analysis* after the clustering procedure to find out the key combinations being responsible for the outcome of the *cluster analysis* and give an interpretational framework for the the combination of the two analyses. This will follow in Chapter 6.[12]

3 The Data

The aim of this thesis is to classify the countries of the world according to the categories *wealth*, *urbanization* and *infrastructure*, hence, data is needed for each country of the world. The theoretical background as to which variables should be included into the analysis has been given in Chapter 2, the task remains to collect the required data for these variables. For the purpose of this paper I consider determined variables at one point in time, namely to cluster the countries according to present data. No time-series analysis will be implemented in this analysis. However, further research can be done to evaluate the evolution of the outcoming clusters over time.
When dealing with data from such different countries, each one with an own national statistical institution, one has to pay special attention to the comparability of the procedures and data. It will not be possible to obtain perfectly comparable data sets, hence, an analysis has to rely on the best available approximations.

The raw data underlying the analysis of this paper is given in Table I in Appendix B and shows data for 204 countries.
Those countries included in the analysis are based on the countries included

[11] Factors can be understood as combinations of variables.
[12] The *factor analysis* procedure will be explained in Chapter 6, for more details on *principal component analysis*, Härdle & Simar (2002) or Johnson & Wichern (1998) are suggested.

in the statistics of the United Nations.[13]

3.1 GDP per capita - PPP

The values for the variable GDP per capita measured in purchasing power parity (*GDP*), are taken from the *CIA World Factbook (2002)*.[14] Basis for this is the nominal GDP divided by the population and by the corresponding PPP estimate for a country.

$$y_P \;=\; \frac{\varepsilon \, P^*}{P}\, y_N \tag{4}$$

y_P being the measure of GDP per capita directly comparable with other GDP per capita due to the PPP adjustment, P being the national price level, ϵ being the nominal exchange rate to the reference or base country, P^* the price level in the base country and y_N the nominal GDP per capita in the country of reference. For PPP to hold, the real exchange rate $\frac{\varepsilon \, P^*}{P}$ should be constant over time.[15] Most PPP estimates utilized to calculate the GDP per capita values underlying the analysis of this paper stem from an extrapolation of PPP estimates published by the UNICP. The PPP estimates are generally reliable for OECD economies, whereas those estimates for developing countries are "often a rough approximation".[16] Even though, the PPP estimates cannot be considered as being securely reliable, they are best approximations. Since nominal GDP values would not yield satisfying comparable measures of well-being across economies, I decided to use these values for GDP per capita based on PPP adjustment for the analysis. An

[13] The source of the listing is
http://unstats.un.org/unsd/demographic/social/population.htm. From that list, East Timor, Gibraltar, Hong Kong, Macao, The Occupied Palestine Territories and Western Sahara are left out due to missing data points or non-compatibility of the data.
Other extraterritorial areas, states or areas with unclear status that are left out of the analysis due to lacking data are Anguilla, Aruba, The British Virgin Islands, Cayman Islands, Christmas Islands, Cocos Islands, Falkland Islands, Farøer Islands, The Gaza Strip, Guernsey, Jersey, The Isle of Man, Mayotte, Montserrat, Niue, The Norfolk Islands, Pitcairn, Saint Helena, Saint Pierre and Miquelon, Taiwan, Tokelau, Turks and Caicos Islands, Wallis and Fortuna and The West Bank.

[14] The *CIA World Factbook* can be found on
http://www.cia.gov/cia/publications/factbook/index.html.

[15] This model is further discussed in Obstfeld & Rogoff (1996). A lot of empirical research has been done on whether the PPP hypothesis holds over time. A discussion on this can be found in Herwatz & Reimers (2002).

[16] See also the Notes and Definitions of the *CIA World Factbook.*

equal attention has to be kept when considering the respective gathering of the data. As mentioned above, each country has its own statistical institutions and thus approaches. The GDP data from the *CIA World Factbook 2002* are mainly year 2001 estimates with some estimates dated earlier.

3.2 Paved Roads

This variable is merely the percentage value of paved roads out of total roads with both values taken from the *CIA World Factbook 2002*. This variable could create problems because there might exist several interpretation as to what kind of streets to include (private roads, farm roads, etc.). But after crosschecking the data with SPIEGEL Weltjahrbuch (2000) and obtaining reasonable results, I decided to include this variable.

3.3 Urbanization

Urbanization gives the percentage of the population living in urban areas. The values are taken from the UN Population Statistics. It has to be mentioned that the definitions of rural and urban areas underly local authorities and can thus differ from country to country. Again, this variable serves as the best approximation.[17]

3.4 Roads per Area

This variable results in the division of the total *km*s of road in a country as taken again from the *CIA World Factbook 2002* divided by the area of a country. Latter variable is fixed and can be taken from various sources. The caveats of the measure for roads holds again.

[17] The data can be found together with the corresponding technical notes on http://unstats.un.org/unsd/demographic/social/hum-set.htm.

3.5 Primacy

The variable *primacy* describes the percentage of the population of one country living in its largest city or metropolitan area. It is almost impossible to obtain unambiguous data for this variable because it is very difficult to set limits as to which population should be included into that of a metropolitan area. Many metropolitan areas, especially in developing countries, are growing very fast, which results in problems estimating the true population. Hence, this variable has to be treated with special care. For purposes of cross-validation, I used various sources and adjusted the values where necessary, to obtain statistically reasonable results. The main source for the population of the cities or metropolitan areas is a data set from a comprehensive study by Henderson (2002a).[18] The cross-validation has been done using data from SPIEGEL Weltjahrbuch (2000) and UN statistics. The underlying overall population in one country is taken from the *CIA World Factbook 2002*.

3.6 Population Density

Population Density is simply the overall population of one country taken from the sources mentioned above divided by its total area.

3.7 Electricity Production per capita

This variable gives the measure of entire electricity produced within one country stemming from all available sources divided by the overall population. The value for the variable electricity production for the respective country is taken from the *CIA World Factbook 2002* with almost all values being year 2000 estimates and some estimates dated earlier. Again, one has to emphasize that a consisted quantification of produced electricity is hard to obtain. Hence, this variable serves once more as the best approximation.

[18] The data can be obtained on http://www.econ.brown.edu/faculty/henderson/ with detailed information on the specific sources and dates of estimation.

3.8 Phone Lines per capita

The infrastructure variable *phone lines per capita* delivers the quantity of used main lines in a country per person. The data is given in the *CIA World Factbook 2002*. In several countries, more main lines are installed, but only those, that are currently in use are being considered and go into the analysis of this paper. The total number of lines per country relies on estimates of the years 1995-2001 and has to be handled with care. Nevertheless, newer data is not available.

3.9 Landlocked

As mentioned before, this variable is the only non-continuous, binary variable. A value of 0 indicates that a country has no access to an ocean, whereas the value of 1 indicates the opposite. It is worth to mention that neither the Caspian Sea nor the Aral Sea count as an ocean, thus Azerbaijan, Kazakhstan, Turkmenistan and Uzbekistan are considered being landlocked in the analysis.

Dealing with huge data sets from different sources and, especially, generated in different countries always bears certain risks. Full compatibility cannot be guaranteed, nevertheless this kind of analysis is of great interest. To obtain better results, the UNICP was created. Even though, the data sets used for the analysis of this paper are taken from a small number of different sources, they are mainly based on UN statistics and therefore provide the best available approximation. This should justify the use of this data and support the results obtained after the analysis.

4 Cluster Analysis

Exploratory procedures are helpful to achieve a better understanding for a given data set, the relationship between the variables and between the observations (Johnson & Wichern (1998)).
A number of techniques exists to identify a formal classification within a sample of observations, which are broadly grouped in the class of vector quantization and dimensionality reduction methods (Hair, Anderson, Tatham &

Balck (1998)). The methodology *cluster analysis* does not require prior information on the classification of the data and is thus the most useful device for the purpose of the research revealed in this paper. In case a prior classification was given and new observations would have to be added to the existing clusters, *discriminant analysis* would be the appropriate technique. But since this paper searches for natural, not predefined clusters among the countries of the world with the focus on *wealth*, *urbanization* and *infrastructure*, *cluster analysis* is the useful procedure. [19]
The aim is to include all available variables to measure the distance between the observations in a $p - dimensional$ input space with n countries to be classified and give a number of clusters c, containing all observations and achieving a small variability within a cluster, but a large variability between the clusters. The objective of the clustering process is thus:

$$G(x) \;:\; R_{n\times p} \;\longrightarrow\; R_{c\times p} \tag{5}$$

with $1 \leq c \leq n$. The border cases $c = 1$ and $c = n$ are not of interest because the former case would group all observations in one cluster and the latter would leave each observations in its own cluster, both not providing new information.
The clustering procedure or function $G(x)$ can be subdivided into two fundamental steps:

1. *Define an appropriate measure of proximity that describes the "closeness" (proximity) between two observations (in this case countries). Greater proximity equals more homogeneity.*

2. *Define an appropriate clustering algorithm that joins the observations into different clusters according to the proximity measure joining homogeneous observations into one cluster and increasing the heterogeneity between clusters.*

Hence, in order two perform a cluster analysis, one has to decide for an appropriate measure of proximity utilized in the procedure and for a clustering algorithm suitable for the given data set and the purpose of the clustering. The following chapters will unveil different choice options.

[19] Further details are given in Härdle & Simar (2002).

4.1 Proximity Measures

Various measurements of *distance* or *proximity* are proposed in the literature. Increasing *distance* indicates objects being further away, whereas larger values of *similarity* describe observations being closer together. This paper is restricted to presenting the most commonly used *distance* measures.
For nominally scaled (especially binary) variables, the so-called *Matching-Type Measures* are used most often. A detailed discussion can be found in Dillon & Goldstein (1984). These measures are, however, not usable for the country data matrix, reason being for omitting the derivation in this paper.
For metrically scaled variables, the *Minkowski metrics* (also called the *L-Norms* are most frequently used as *distance measures* and obtained by

$$d_{i,j} = \left[\sum_{k=1}^{p} |X_{ik} - X_{jk}|^r \right]^{\frac{1}{r}}. \tag{6}$$

$d_{i,j}$ gives the value for the distance between observations i and j with X_{ik} being the value of the ith observation of variable k, $i = 1, ..., n$ and $k = 1, ..., p$.[20]
The most commonly used *Minkowski metrics* are the *city-block metric*

$$d_{i,j} = \sum_{k=1}^{p} |X_{ik} - X_{jk}| \tag{7}$$

and the *Euclidean distance*[21]

$$d_{i,j} = \left[\sum_{k=1}^{p} (X_{ik} - X_{jk})^2 \right]^{\frac{1}{2}}. \tag{8}$$

Sometimes, the *squared Euclidean distance* is also used:

$$d_{i,j} = \sum_{k=1}^{p} |X_{ik} - X_{jk}|^2. \tag{9}$$

[20]In this study, the "i's" are the countries with $i = 1, ..., 192$ and the "k's" are the variables with $k = 1, ..., 9$.

[21]In matrix notation, the *Euclidean distance* can be written as $d(\mathbf{X}_i, \mathbf{X}_j) = \sqrt{(\mathbf{X}_i - \mathbf{X}_j)'(\mathbf{X}_i - \mathbf{X}_j)}$, where $\mathbf{X}_i$ and $\mathbf{X}_j$ are p-dimensional vectors corresponding to the ith and jth observation. The statistical distance between two observations would be of the form $d(\mathbf{X}_i, \mathbf{X}_j) = \sqrt{(\mathbf{X}_i - \mathbf{X}_j)'\mathbf{S}^{-1}(\mathbf{X}_i - \mathbf{X}_j)}$, where $\mathbf{S}$ contains the sample variances and covariances. However, since the clusters are not known in advance, this quantity is not computable and thus the *Euclidean distance* is used (Johnson & Wichern (1998), p. 728).

The use of each one of the *Minkowski metrics* depends on the emphasis one wants to put on those observations that are further away from others. Utilizing the *city-block metric*, the absolute value of the distance between two observations is measured. Therefore, all distances are weighted equally. The *Euclidean distance* puts more weight on those observations that are further away, by squaring the respective distances. A detailed discussion on these distance measures can be found in Dillon & Goldstein (1984) or in Backhaus, Erichson, Plinke & Weiber (1996).
Another proposed proximity measure is the *Mahalanobis distance*

$$D^2 = (\mathbf{X}_i - \mathbf{X}_j)'\mathbf{S}^{-1}(\mathbf{X}_i - \mathbf{X}_j) \tag{10}$$

where $\mathbf{X}_i$ and $\mathbf{X}_j$ are the vectors of measurement on objects i and j and $\mathbf{S}$ is the pooled within-group covariance matrix (Dillon & Goldstein (1984)). Standardizing the data first and computing the *Euclidean distance* on this standardized data set yields the same results as the *Mahalanobis distance*.

Calculating the distances between all observation yields a $n \times n$ distance matrix $\mathbf{D}$ utilized with the respective clustering algorithm to determine the clusters.

The choice of the proximity measure also depends on the choice of the clustering algorithm utilized for the analysis. Those are presented in the next section.

4.2 Clustering Algorithms

The group of clustering algorithms can, at a first step, be subdivided into two main categories, the *hierarchical* and the *non-hierarchical* or *partitioning* techniques. Former proceed in a way that either all observations form separate clusters at the beginning and are joined to form new clusters in a successive way, or all observations form one cluster at the beginning and are subdivided into more and more clusters successively. However, once an observation is assigned to one cluster, it remains in this cluster (or sub-cluster stemming from a division). That is not the case in the *non-hierarchical technique*. Using this, observations are moved around in a given number of clusters in an iterative way until a given objective function determining the similarity within clusters is maximized. In this procedure, observations are allowed to switch clusters in the iterative process. Both categories of algorithms have advantages and disadvantages with the computation of the non-hierarchical procedures, in general, being more cumbersome. But as a final result, one obtains a set of clusters with all observations included in them.

4.3 Hierarchical Clustering Procedures

The category *hierarchical clustering procedures* can initially be subdivided into *agglomerative* and *divisive* procedures. The *agglomerative* procedures start at an initial partition with each observation being one separate cluster, and new clusters are obtained by joining observations, and then clusters of observations, consecutively. The *divisive* procedures start at a partition with just one cluster containing all observations and dividing this cluster into an increasing number of clusters in following steps. The way the agglomerative hierarchical algorithms differ is mainly characterized by the way distance matrix $\mathbf{D}$ is used. All agglomerative hierarchical procedures start with joining those two observations into one cluster, which are separated by the shortest distance, i.e. the smallest value $d_{i,j}$ in the distance matrix $\mathbf{D}$. After the first clustering step, a new distance matrix $\mathbf{D}$ exists, which is of dimension $n-1$ and contains the distances between all observations and between the cluster of the two joint observations and all other observations. The way this distance between the cluster(s) and the other observations or clusters is calculated is the source of differentiation between the algorithms. A choice of the most frequently used agglomerative algorithms follows.

4.3.1 Single Linkage Algorithm

The *single linkage method* is also called *nearest-neighbor method*, the reason being that the new distance between a cluster and an observation is calculated as the minimum of the distances between each observation within the cluster and that outside the cluster. If objects i and j are joined in one cluster, the new distance between this cluster and the object l is calculated in the *single* *linkage method* the following way:[22]

$$d_{ij,l} = min(d_{i,l}, d_{j,l}). \tag{11}$$

The *single linkage* algorithm combines the two objects or clusters with the smallest distance between its closest neighbors. The main shortcoming of this algorithm is the so-called *chaining* property. *Single linkage* tends to build too large groups due to its weakness two detect poorly separated clusters. On the other hand, this property helps to detect outliers.

4.3.2 Complete Linkage Algorithm

The *complete linkage* algorithm, in contrast, combines those objects or clusters into a new cluster, which have the shortest distance in the distance matrix $\mathbf{D}$, but latter being calculated by the furthest distance between the observations within one cluster and an outside observation. Hence, it is also called the *furthest neighbor method*. The new distance to object l after joining objects i and j is computed by[23]

$$d_{ij,l} = max(d_{i,l}, d_{j,l}). \tag{12}$$

Both, the *single linkage* and the *complete linkage* algorithms are independent of the *distance measure* used in the process as long as the ordering of distances remains. A discussion of the different algorithms can be found in Härdle & Simar (2002), Gordon (1999) or Johnson & Wichern (1998).[24]

4.3.3 Ward's Error Sum of Squares Method

Ward (1963) proposed one clustering algorithm that is not based on joining those objects or clusters with the smallest distance between them, but those where the loss of information resulting from grouping observations or clusters is smallest based on the deviations of every observation from the mean of its

[22] If two clusters are joined, the resulting distance would be $d_{ij,lm} = min(d_{i,l}, d_{j,l}, d_{i,m}, d_{j,m})$. A detailed derivation of the distance matrices with simple and illustrative examples is given in Dillon & Goldstein (1984), pp. 168ff.

[23] The distance $d_{ij,lm}$ would be calculated respectively as in the footnote above.

[24] A computational approach using the Software Environment *XploRe*®, which is also utilized for this analysis, can be found in Mucha & Sofyan (2000).

cluster (Dillon & Goldstein (1984)). For the *Ward method*, the underlying distance measure is the *within-cluster sum of squares* calculated by

$$d_{ij}^2 = \sum_{k=1}^{p} (x_{jk} - v_{ik})^2 \tag{13}$$

with the following notation:
c, number of clusters (i)
n, number of objects to be classified (i.e. countries j=1,2,...,192)
p, number of variables (i.e. k=1,2,...,9)
x_{jk}, value of the kth variable on observation j
v_{ik}, the cluster mean of the kth variable in cluster i.[25].

The resulting *dissimilarity index* from the *Ward* procedure is the *Ward variance* obtained after every step in the clustering process, i.e. after joining clusters consecutively:

$$E = \sum_{i=1}^{c} \sum_{j=1}^{n_i} d_{ij}^2. \tag{14}$$

This measure E is called the *error sum of squares*. According to the *Ward* procedure, those two observations or clusters are combined into one cluster that increase the value of E the least.[26]
The *Ward* procedure has a different approach to the two *linkage* algorithms described above in that it does not combine those observations or clusters that are separated by the shortest distance, but whose combination has the least impact on a combined measure of within-cluster homogeneity. The *Ward* method is used preferably in most empirical research and is far less sensitive to *chaining* mentioned above.

[25]It is calculated the following way: $v_{ik} = \frac{1}{n_i} \sum_{j \in C_i} x_{jk}$, where n_i is the number of observations in cluster i and $j \in C_i$ those observations contained in cluster i
The notation is taken from Romesburg (1984) but slightly adapted to be consistent with the notation of this paper.
[26]An easy-to-follow empirical approach is given in Backhaus, Erichson, Plinke & Weiber (1996).

4.3.4 Graphical device: The Dendrogram

There exists one useful graphical device to represent the stepwise clustering process of all three algorithms defined above, which is called the dendrogram and looks as follows (for a simple random example of eight observations):

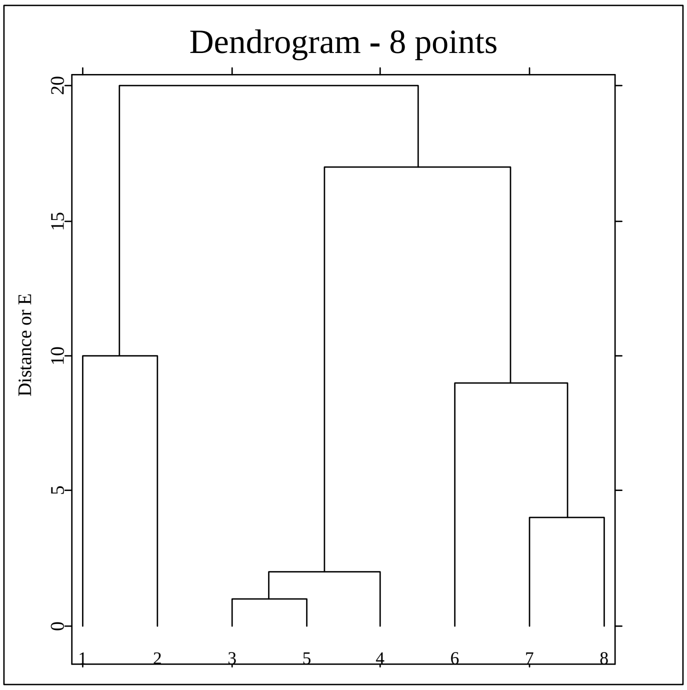

Figure 1: Example of a Dendrogram

The horizontal axis contains the observations that are joined sequentially and the vertical axis gives the value of the distance between those observations or clusters that are joined in the case of the *linkage* algorithms, and it gives the value of E, the *error sum of squares* after the respective clustering step for the *Ward* approach. The dendrogram shows in an illustrative way, what observations and clusters are combined at what stage.

4.3.5 Other Agglomerative Hierarchical Procedures

Several other agglomerative hierarchical procedures have been proposed. However, most of them are being used less in practice.
One algorithm that is often mentioned in the literature is the *average linkage* algorithm which takes the distance between two clusters as the average between all items in each one of them.
Other algorithms are the *Centroid* algorithm, the *Median* algorithm and the

flexible method. Without going further into detail, the basic properties shall be given shortly. The way the distance between two objects or clusters that are to be grouped is measured depends on the algorithm, as described above. If clusters or observations i and j are joined in one cluster, its distance to the observation or group l can generally be written as

$$d_{ij,l} = \delta_1 d_{i,l} + \delta 2 d_{j,l} + \delta_3 d_{i,j} + \delta_4 |d_{i,l} - d_{j,l}| \tag{15}$$

with notation as above (Mucha & Sofyan (2000)). In this case, the mentioned algorithms would define the δs the following way:

Algorithm	δ_1	δ_2	δ_3	δ_4
Single linkage	$\frac{1}{2}$	$\frac{1}{2}$	0	$-\frac{1}{2}$
Complete linkage	$\frac{1}{2}$	$\frac{1}{2}$	0	$\frac{1}{2}$
Average linkage	$\frac{n_i}{n_i+n_j}$	$\frac{n_j}{n_i+n_j}$	0	0
Centroid	$\frac{n_i}{n_i+n_j}$	$\frac{n_j}{n_i+n_j}$	$-\frac{n_i n_j}{(n_i+n_j)^2}$	0
Median	$\frac{1}{2}$	$\frac{1}{2}$	$-\frac{1}{4}$	0
Ward	$\frac{n_i+n_l}{n_i+n_j+n_l}$	$\frac{n_j+n_l}{n_i+n_j+n_l}$	$\frac{-n_l}{n_i+n_j+n_l}$	0
Flexible method	$\frac{1-\beta}{2}$	$\frac{1-\beta}{2}$	β	0

Table 1: Different Agglomerative Hierarchical Clustering Algorithms[27]

Bergs (1981) found out that the *Ward* procedure, in general, found very reasonable partitions and was more efficient than the other algorithms. This is the reason why some algorithms are treated only shortly in this section and also one reason why the *Ward* algorithm will be used mainly throughout the empirical analysis following in this paper.

4.3.6 Divisive Algorithms

Divisive algorithms work in the opposite direction to the *agglomerative* methods. They start at an initial partition with just one cluster containing all observations. The algorithms sub-divide the clusters in a stepwise optimal process similar to the *agglomerative* techniques. A discussion on these techniques can be found in Gordon (1999), p. 90. However, the *divisive algorithms* are found less in the literature and empirical work, even though Gordon (1999) mentions, that the use should sometimes be preferred since researchers are mainly interested in larger clusters.

[27]The table is taken from Mucha & Sofyan (2000) and adjusted to the notation of this paper.

4.4 Non-Hierarchical Clustering Procedures

Non-hierarchical or *partitioning* algorithms are another approach to find an existing but not known grouping within a given data set. In contrast to the *hierarchical* procedures, these do not increase or decrease the number of clusters in subsequent steps. An initial number of clusters has to be given as a starting point. After that, the observations are interchanged among the clusters until an optimal allocation is found according to a prespecified algorithm. These algorithms do not yield consistent results when clusters merge step-by-step. Observations do not have to remain in clusters when these are merged to become larger. Therefore, it is useful to perform a *hierarchical* cluster analysis in a first step to determine an optimal or desired number of clusters, and then proceed with a *non-hierarchical* procedure to determine the respective members, i.e. observations, belonging to each cluster as Hair, Anderson, Tatham & Balck (1998) suggest it. An important difference to the *hierarchical* procedures is that observations are allowed to change clusters in the clustering process, i.e. after a new number of clusters has been defined and the clustering process took place accordingly.
Several *non-hierarchical* clustering algorithms have been proposed in the literature, however, the following subsection shall be limited to presenting those utilized or intended to be used in the empirical analysis hereafter.[28]

4.4.1 K-Means

An often proposed and frequently used *non-hierarchical* procedure is the *K-Means* clustering method. The aim of this procedure is to allocate the observations iteratively to a specified number of clusters such that overall distances between the observations and their respective cluster means, the *centroids*, are minimized. As a starting point, this algorithm requires two specifications:

1. *Define a number of clusters c.*
2. *Give an initial partition, i.e. define which cluster each observation belongs to.*

[28]For a more detailed discussion on several *non-hierarchical* techniques, consult Mucha & Sofyan (2000), or for a more technical overview, Gordon (1999).

It is useful to begin with a *hierarchical* procedure before using the *K-Means* method to define a reasonable number of clusters. For the specification of the initial partition, several methods have been suggested. MacQueen (1967) proposed a random allocation among the clusters. It has to be kept in mind, however, that the initial partition can have an effect on the outcome of the iterative process. Therefore, the initial partition could preferably be based on results obtained before, e.g. from a *hierarchical* procedure. Alternative methods suggest predefining *seed points* evenly across the data range and combine those objects in an initial cluster that are closest to the respective *seed point* (Gordon (1999), pp. 41f.).
Once having defined the number of clusters and the initial partition, the *within-cluster variance* or *error component* of the partition can be calculated. The *Euclidean distance between* an observation j and the cluster mean i can be calculated as

$$d_{j,i} = \left(\sum_{k=1}^{p} \left[x_{jk} - \bar{x}_{ik} \right]^2 \right)^{\frac{1}{2}} \tag{16}$$

where the notation is as before.[29] The *error component* of this partition can then be defined as

$$E\left[P(\mathbf{n}, \mathbf{c})\right] = \sum_{i=1}^{c} \sum_{j=1}^{n} \delta_{ji} d_{j,i}^2 \tag{17}$$

where $P(\mathbf{n}, \mathbf{c})$ defines a partition of $\mathbf{n}$ observations into $\mathbf{c}$ clusters and δ_{ji} is an indicator function that takes the value 1 if the jth observation is in cluster i an 0 otherwise.[30] The *K-Means* algorithm works iteratively. After the *error component* of the initial partition has been computed, it is calculated for each observation, whether E diminishes in case the observation is shifted from one cluster to another. If this is true, the observation is shifted to that new cluster and new cluster means are calculated and the whole procedure starts again until no improvement of the *within-cluster variance* can be reached. The final result is the optimal allocation of the n observations to the c clusters.

An extension to the ordinary *K-Means* method is the use of the *adaptive K-Means* which includes weighted distances between each observation and its cluster mean rather than weighing all distances with equal weight.[31]

[29] The cluster mean $\bar{x}_{ik}$ is the same as the v_{ik} from (13).

[30] A discussion can be found in Dillon & Goldstein (1984) and Mucha & Sofyan (2000). The notation is adjusted to this paper.

[31] The empirical analysis following in this paper will be restricted to the use of the

4.4.2 Hard C-Means

Another iterative procedure to allocate n observations into c clusters is the *hard C-Means* method proposed by Ruspini (1969). The algorithm works similar to the *K-means* algorithm, yet the iterative process differs slightly. Same as above, the *Euclidean distance* between each observation an its cluster mean is calculated as in equation (13). The v_{ik} can alternatively be computed as

$$v_{ik} = \frac{\sum_{j=1}^{n} \chi_{ij} x_{jk}}{\sum_{j=1}^{n} \chi_{ij}} \tag{18}$$

where χ_{ij} is an indicator function taking the value 1 if observation j is in cluster i and 0 otherwise. All χ_{ij}s define a $n \times c$ matrix $\mathbf{U}$, the partition matrix. For the c clusters and n observations there are

$$\eta_U = \left(\frac{1}{c!}\right)\left[\sum_{i=1}^{c} \binom{c}{i} (-1)^{(c-i)} i^n\right] \tag{19}$$

different possible partition matrices $\mathbf{U}$. Thus, the objective is to find an optimal partition U^*. The objective function is

$$J(U, \mathbf{v}) = \sum_{j=1}^{n} \sum_{i=1}^{c} \chi_{ij} d_{ij}^2 \tag{20}$$

which has to be minimized with respect to U and $\mathbf{v}$ yielding U^* and $\mathbf{v}^*$. $\mathbf{v}$ is the $c \times p$ matrix of cluster centers. The algorithm then follows an eight-step procedure:

1. *Start with the predefined centroids and partition and calculate all* d_{ij}*s.*

2. *Given the predefined cluster centers (call them* v^0*), allocate the observations to those clusters for which the distance to the centroid is smallest and obtain* U^0*.*

3. *Compute* $J(U^0, v^0)$ *and call it* J^0*.*

4. *Calculate the new cluster centers* v_{ik} *given by* U^0 *and obtain* v^1*.*

ordinary *K-Means* method. Hence, a more detailed discussion is left out. It can be found in Mucha & Sofyan (2000) or Gordon (1999).

5. *Recalculate the distances* d_{ij} *and allocate them to the closest cluster centers to obtain* U^1.
6. *Compute* $J^1 = J(U^1, v^1)$.
7. *Repeat the steps 3, 4 and 5 until the changes from* J^h *to* J^{h+1} *are below a tolerance level. The resulting partition* J^h *corresponds to* U^*.[32]

The result is a clustering of the n observations into c clusters.

4.4.3 Fuzzy C-Means

The *Hard C-Means* method described above is called a *crisp* method because it measures the distance between each observation and all cluster centers but allocates each observation determinedly to only one cluster. Thus, the defined clusters are non-overlapping. The methodology *Fuzzy C-Means* allows cluster regions to overlap and determines degrees of belonging to each cluster for every observation. Hence, the *Fuzzy C-Means* algorithm yields a $n \times c$ matrix of degrees of membership. The degree of membership to cluster i for observation j is denoted as $\mu_{ij} \in [0, 1]$, with the straightforward restrictions

$$\sum_{i=1}^{c} \mu_{ij} = 1 \quad , for\ all\ j = 1, 2, ..., n \tag{21}$$

$$0 < \sum_{j=1}^{n} < n \quad , for\ all\ i = 1, 2, ..., c. \tag{22}$$

With this, one can define a family of fuzzy partition matrices

$$M_{fc} = \left\{ U_f \middle| \mu_{ij} \in [0, 1]; \sum_{i=1}^{c} \mu_{ij} = 1; 0 < \sum_{j=1}^{n} < n \right\} \tag{23}$$

where any U_f is a fuzzy partition. In contrast to the previous matrix U, which contained only values of 0 and 1, these matrices U_f contain values between 0 and 1 indicating the respective degrees of membership. Again, the task is to find an optimal U_f^*. The distance is the same used in equation (13). In addition, a new *fuzziness parameter* m is required with $m \in [1, \infty)$. The *fuzziness parameter* is also used as a weighting parameter to compute

[32] The algorithm is taken from Ross (1995) and given in short form in Cattaneo, Diaz-Bonilla, Robinson & Thomas (2000).

the new cluster centers differing from those of the *Hard C-Means*. These are obtained by

$$v_{ik} = \frac{\sum_{j=1}^{n} \mu_{ij}^{m} x_{jk}}{\sum_{j=1}^{n} \mu_{ij}^{m}} \tag{24}$$

with the same notation as before. The new objective function yielding U_f^* and v^* after minimization, is

$$J_m(U_f, v) = \sum_{j=1}^{n} \sum_{i=1}^{c} \mu_{ij}^{m} d_{ij}^{2}. \tag{25}$$

The algorithm follows this procedure:

1. *Again, define the number of clusters c ($2 \leq c < n$), fix the initial partition matrix U^0 and the terminal condition $\varepsilon > 0$ and set the parameter m.*[33]

2. *Compute the c cluster centers $\left\{ v_{ik}^{(r)} \right\}$ for each step.*

3. *Compute the partition matrix $U^{(r)}$ at each step:*

$$\begin{gathered}
\mu_{ij}^{(r+1)} = [\textstyle\sum_{i=1}^{c} (\frac{d_{ij}^{(r)}}{d_{hj}^{(r)}})^{\frac{2}{m-1}}]^{-1} \quad , \ for\ I_j = \varnothing \\
\mu_{ij}^{(r+1)} = 0 \quad , \ for\ all\ clusters\ i\ where\ i \in \tilde{I}_j \ , \\
with\ I_j = i | d_{ij}^{(r)} = 0, \\
\tilde{I}_j = 1, 2, ..., c - I_j \\
and\ \textstyle\sum_{i \in I_j} \mu_{ij}^{(r+1)} = 1.
\end{gathered}$$

4. *If $\left|\left|U^{(r)} - U^{(r+1)}\right|\right| \leq \varepsilon$, stop; otherwise return to step 3.*

This procedure converges to a local minimum or saddle path solution (Mucha & Sofyan (2000)). The result obtained is a partition matrix U_f allocating each observation to one cluster, namely the one with the largest degree of membership. In case the distances to two cluster centers are equivalent, a new, outlying cluster is defined. Since the computation is somewhat cumbersome due to the large dimensions of the matrix U that has to be recomputed iteratively, even with newer computer programs one might reach limits of feasibility surpassing a number of data points.

[33]Note that if $m \longrightarrow 1$, the algorithm approaches the *Hard C-Means* algorithm with the degrees of membership only taking values of 0 and 1. If $m \longrightarrow \infty$, the membership assignments become more fuzzier, and the objective $J_m \longrightarrow 0$.

5 The Empirical Analysis

The relevant theoretical aspects have been discussed in detail, as well as the sources of the data utilized in the analysis. Therefore, the attention can focus again on the questions set forth at the beginning, namely the interest of the research undertaken in this paper. How can we classify the countries of the world reasonably, from the perspective of *wealth*, *urbanization* and *infrastructure*, parameters that determine to a large extent well-being of mankind? What policy conclusions can we draw from such a classification?
The following empirical analysis should answer these questions. As suggested above and throughout the literature, it is useful to perform a *hierarchical* cluster analysis as a first step. The exploratory technique cluster analysis does not necessarily require common scaling of the variables, however, this can have severe impact on the outcome.

5.1 Ward Clustering with Raw Data

As an initial step I performed a cluster analysis using the *Ward* procedure on the raw data matrix given in Table I in Appendix B. The computation was done using the quantlet `t = agglom (d, "WARD", 15)` in the software package *XploRe*®,[34] with d being the *Euclidean* distance matrix. The results of this clustering process using the numbers of 8 and 15 clusters is given in Table II in Appendix C. The result shows that using only 8 clusters, the clustering is merely an ordering according to the GDP per capita level, which is included in the table for illustration, with some cutting values defining the cluster borders. Specifying 15 clusters does not entirely follow the ordering according to GDP per capita, yet it does so to a great extent, especially in the clusters containing countries with higher values of GDP per capita (clusters 7-15). Only in those clusters, in which GDP per capita does not differ so much in absolute values and fluctuates on lower levels (clusters 1-6), some countries are grouped in clusters with a higher average GDP per capita, even though the countries themselves have a lower value than those with the highest GDP per capita value of the cluster before.[35]
The result with this bias is straightforward since the *Euclidean* distance calculated between every two observations includes all absolute values of the

[34] *XploRe*® is a statistical software environment. The macros used in the software to compute specified statistical procedures are called *quantlets*. This software environment is used for the analysis of this paper.

[35] Examples are Guinea, Ghana, St. Lucia, The FYR of Macedonia.

differences between every variable. Looking again at the raw data in Table I in Appendix B, shows that the variable *GDP* has the largest scale of the variables included. Hence, not transforming the data results in a biased clustering towards this variable.
The heavy bias motivates the use of standardized variables. There are many possibilities to transform variables in order to achieve different results. All depends on how one wants to weigh the different variables. The analysis of this paper wants to take the categories *wealth*, *urbanization* and *infrastructure* equally into account and thus - even though there are five infrastructure variables, four population variables and only one wealth variable - puts equal emphasis on all variables included. This happens by standardizing the variables according to

$$x_{jk}^{stand.} = \frac{x_{jk} - \bar{x}_k}{\sigma_k} \tag{26}$$

where $\bar{x}_k = \sum_{j=1}^{n} x_{jk}$, σ_k the standard deviation of k and the notation as before. The mean of the respective variable is subtracted from each data point in the data matrix and the difference is divided by the respective standard deviation. The new, standardized data matrix is given as Table III in Appendix D.

5.2 Detecting Outliers

The first step in the analysis is to detect outliers that would distort the results of the analysis in an undesired way. *Agglomerative hierarchical* procedures have been identified to be useful for outlier detection, and among these, especially the *single linkage* algorithm. Hence, I performed a *single linkage* cluster analysis for the given standardized data set for the choice of 8 and 15 clusters. The quantlet used for the computation is `t = agglom (d, "SINGLE", 8)`.[36] The results of this clustering procedure are given in Table IV in Appendix E, and the dendrogram is shown in Figure 2.
The dendrogram and the results from Table IV both reveal clearly the drawbacks of the *single linkage* algorithm. Chaining is evident in the outcome of the computation with this algorithm. Specifying 8 clusters, joins all observations into one, namely the first cluster, except for the last 8 observations,

[36] `d` is again the *Euclidean* distance matrix and for the analysis of 15 clusters, this value is used in the quantlet instead of 8.

detecting separate groups for each of the last seven countries. Using 15 clusters, a large number of countries is grouped in cluster 5, and again, the last seven countries each have a cluster of their own.
The appearance of severe chaining in the analysis, however, gives some information on the underlying data set. Making use of the standardized data, a number of countries seem to be close together, meaning that the distances between its data points are relatively small. Hence, natural clusters are not sharply detached from each other, but rather smoothly.
The results and the fact that natural clusters to be found within the data set are not sharply separated, make the use of the *single linkage* algorithm inappropriate. I will therefore follow with the clustering process using the *Ward* algorithm which is less sensitive to chaining.

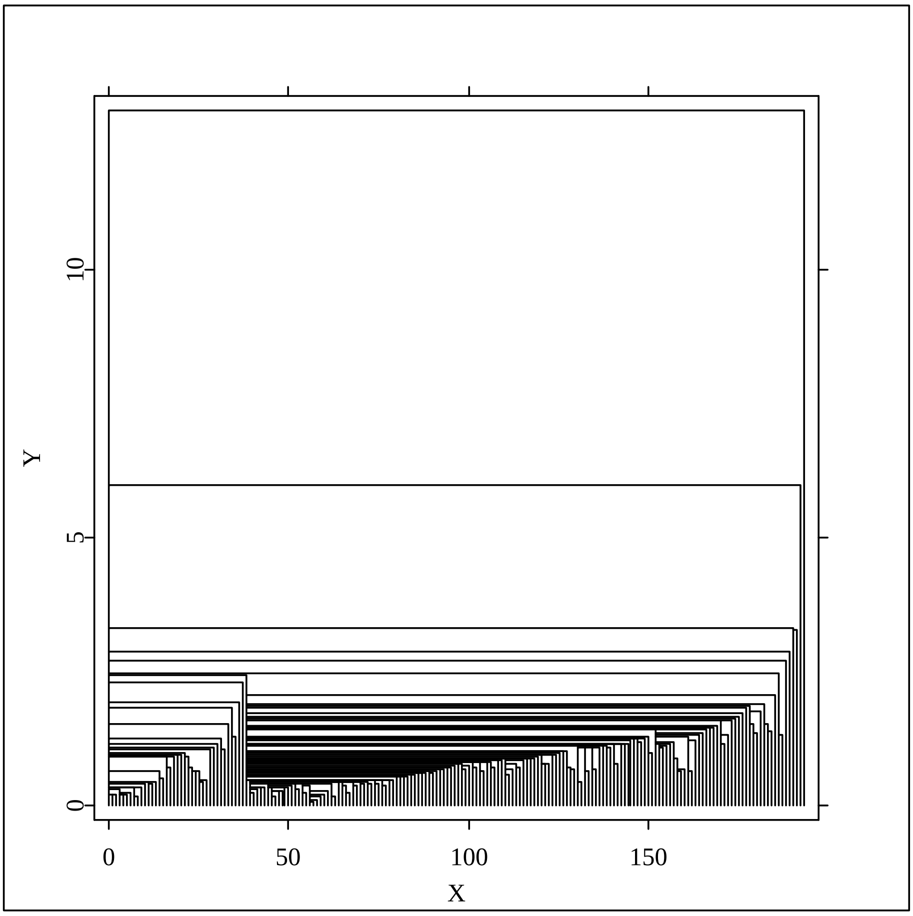

Figure 2: Single Linkage Dendrogram for Standardized Data

Again, the quantlet used is `t = agglom (d, "WARD", 8)`, where `d` is the *Euclidean* distance and 8, 9 and 10 used respectively for the number of clus-

ters. The results are given in Table V in Appendix F. One outlier is clearly identifiable, Monaco. This is very intuitive, since Monaco is a city-state and thus an unbiased comparison with other countries is difficult. For this reason, Monaco will be left out of the ongoing analysis to obtain more robust results! In this range of clusters, another outlier cannot be detected. Nevertheless, since the task of specifying the number of clusters useful for the analysis and interpretation is yet to come, we move to larger but still reasonable number of clusters to detect more outliers.
The same quantlet as above is used on the standardized data leaving out Monaco, and the clustering procedure is performed for 8, 9, 10, 12 and 15 clusters. The results from this computation are given in Table VI in Appendix G.
The Table identifies another outlier consistently. It is Singapore, another city-state. Higher numbers of clusters are not reasonable for the analysis because it would simply yield too many, at the end not usefully interpretable clusters. Hence, Singapore will also be left out of the analysis, which will be performed with the remaining sample of 192 countries.

5.3 Choice of the Number of Clusters

Defining the number of clusters is a prerequisit for the clustering procedure. The interpretation of the results depends to a large extent on the choice of clusters c. Hence, it is not only a statistical question to determine the number of clusters used for the analysis but also a question of the interpretability and usefulness of the obtained results from different values of c.
Gordon (1999) states two approaches for choosing a number of clusters c, one informal and one formal. The informal approach would be to compare the outcome of different clustering procedures with different values of c and analyze what occurs during the stepwise clustering process. For the formal approach, a number of so-called *stopping rules* are discussed that are based on computations of the within-cluster variance and the between-cluster variance. The result of the discussion, however, does not give convincing and consistent results to decide for a specific algorithm, and even combining different algorithms does not always lead to robust results.[37]

[37] The same criticism holds for the *cluster validity analysis* which can take place after defining a number of clusters and performing the descriptive analysis of the obtained clusters. *Cluster validity analysis* checks if the clusters derived throughout the analysis are in fact optimal and correct. But the algorithms so far proposed in the literature, which are used for this kind of analysis lack in robustness (Gordon (1999), pp. 183ff.).

Since the interpretability of the clusters derived from the analysis of this paper should be the key aim of research, an informal approach to assess the optimal number of clusters c to be included in the analysis is reasonable.
In order to determine useful numbers of clusters a cluster analysis using the *Ward* method is done for a variety of clusters c using the 192 countries finally included in the analysis. The results are given in Table VII in Appendix H, and the dendrogram resulting from the *Ward* clustering of the standardized data of 192 countries is shown in Figure 3.

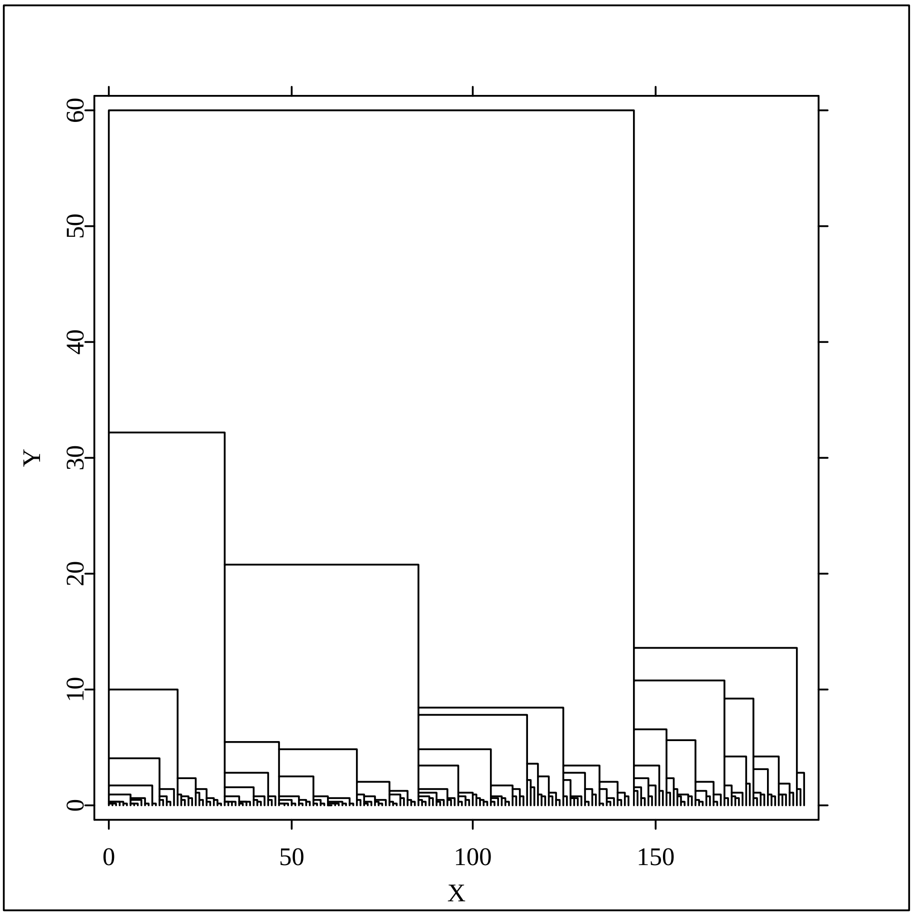

Figure 3: Ward Dendrogram for Standardized Data without Monaco and Singapore

The obtained result gives a first useful clustering of the countries. Using 4, 5 or 6 clusters yields a rough clustering, i.e. a small number of clusters, each one containing a large number of countries. The splitting of the clusters only happens in those clusters comprising countries with higher levels of GDP per capita, infrastructure and urbanization. Thus, considering a cluster analysis

with a small number of clusters c does not lead to satisfyingly interpretable results with the special focus on classifying developing countries in a more precise way. The division between 7 and 8 clusters shows an interesting partition of a cluster containing countries with relatively higher levels of variables of the three different categories. Further steps show a further subdivision of those clusters containing more developed countries.[38] Therefore, the number of clusters $c = 8$ provides a reasonable size that allows a rich analysis and interpretation of the results with the focus of this paper.
To obtain even further results I perform the analysis for another, larger number of clusters c. Therethrough, the results will be comparable and one will be able to see what additional information can be withdrawn. Looking again at Table VII, further cluster divisions (i.e. $c > 8$), occur mostly among intermediate clusters, i.e. those clusters that mainly stem from clusters 4 and 5 in the eight-clusters-solution. The step from 12 to 15 clusters shows an interesting development since cluster 3, one that contains relatively "less developed" countries, in the twelve-clusters-solution is subdivided threefold in that step. Hence, the 15-clusters-solution presents another interesting benchmark for the purpose of this analysis.
As a result, the number of clusters $c = 8$ and $c = 15$ will be used for the following analysis.

5.4 Descriptive Analysis for 8-Clusters- and 15-Clusters-Solution

The *Ward* procedure already gives a first clustering of the data. The result can be used to perform a descriptive analysis of the obtained clusters. This will be done in the following subsection. The entire analysis will consist of three parts. First the *hierarchical agglomerative Ward* method will be used and a descriptive analysis will be done making use of the obtained results. Thereafter, two *non-hierarchical* methods will follow, both described above. The *K-Means* method will be used in combination with the number of clusters derived before, and, a fuzzy clustering will be done using the *Fuzzy C-Means* approach. Latter will reveal some difficulties with the underlying data set. The combination of those *hierarchical* and *non-hierarchical* approaches is suggested in the literature to obtain good results.[39]

[38]This term is used here to merely name those countries with relatively lower levels of *wealth*-, *infrastructure*- and *urbanization*-variables.
[39]For a discussion of the combined use of *hierarchical* and *non-hierarchical* approaches as best practice consult Hair, Anderson, Tatham & Balck (1998).

5.4.1 Descriptive Analysis for *Ward* Approach

In Table VIII in Appendix I, the two cluster partitions $c = 8$ and $c = 15$ are isolated and the before mentioned categories defined by the UN and used by other institutions are included. These categories are $LLDC$ defining the *least developed countries*, LDC, the *less developed countries*, $OECD$ for the OECD economies and finally the special group of $USSR/EE$, the former socialist Transition Economies once belonging to the USSR or being in Eastern Europe. This partition yields very interesting results. The clustering procedure seems to detect those categories predetermined by the UN. The LLDCs and the LDCs are entirely in the clusters $c = 1, 2, 3, 4, 7$ in the 8-clusters-solution and the developed countries are predominantly grouped in the remaining clusters. The clustering even detects the subgroup of USSR/EE countries and groups a large share of them in cluster 2. For the 15-clusters-solution, the LLDCs and LDCs are grouped in clusters $c = 1, 2, 3, 4, 5, 6, 7, 8, 9, 14$ and the developed countries predominantly in the remaining clusters. However, the outcome gives interesting new results that are more precise than the classification into LLDCs, LDCs and developed countries.

First, there is no division between the LLDCs and the LDCs. Thus, a grouping of the countries with the focus on *wealth*, *urbanization* and *infrastructure* making use of the variables used in this analysis, does not justify the subdivision of developing countries into the LLDCs and LDCs which is currently in use. The isolated cluster containing the largest share of the USSR/EE countries is an interesting finding of the clustering process. Descriptive analysis will be needed to give reasons for these countries to fall in a different cluster than USSR/EEs like Lithuania or Slovenia. Moreover, descriptive analysis will be needed to analyze the cluster 7 (or 15 respectively in the 15-cluster-solution) containing mostly LDCs. The specific partitioning of the developed countries will also be of relevance and part of the descriptive analysis.

When undertaking a descriptive analysis of the different obtained clusters, the interest is especially on the cluster centers of each cluster, since the observations are grouped around these.[40] Hence, the computation of the *z-scores* is of great interest. The *z-scores* are the statistical mean of the clusters in standardized terms, i.e. the mean of the standardized data. A table of the *z-scores* for the 8-clusters-solution is given in Table 2. The results are plotted

[40] The cluster centers are computed as the statistical mean of each cluster.

in Figure 4.

Cluster	GDP	PAV	URB	RPA	PRIM	POPD	EPPC	PHL	LL
1	-0.733	-1.072	-1.177	-0.489	-0.608	-0.329	-0.494	-0.841	-1.914
2	-0.474	0.948	-0.436	-0.378	-0.190	-0.405	-0.223	-0.397	-1.914
3	-0.656	-0.715	-0.734	-0.432	-0.454	-0.255	-0.555	-0.751	0.520
4	-0.218	-0.039	0.342	0.043	0.227	0.036	-0.196	-0.105	0.520
5	1.537	1.285	0.720	0.886	-0.057	0.214	0.482	1.576	-0.356
6	2.097	0.233	1.070	-0.325	0.442	-0.620	3.362	1.990	0.520
7	0.677	0.882	1.268	-0.051	2.059	0.503	0.925	0.593	0.520
8	1.448	1.226	1.666	5.226	-0.713	5.500	1.072	1.578	0.520

Table 2: *Z-Scores* for 8 Clusters obtained by *Ward* Method[41]

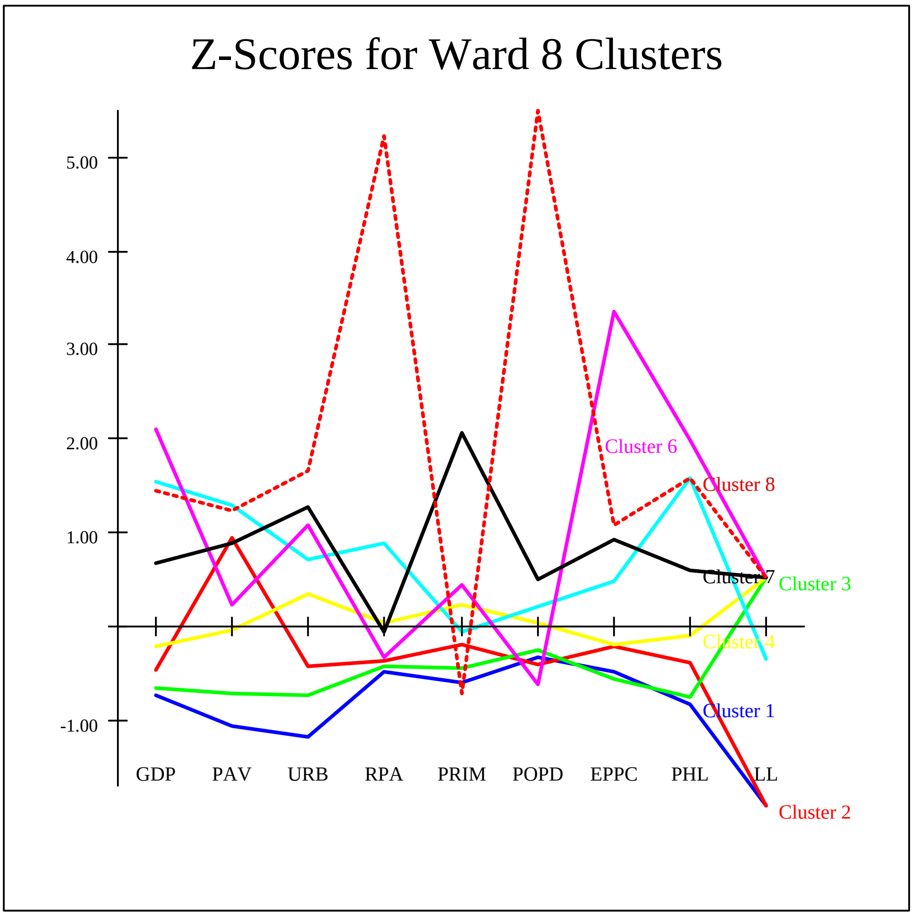

Figure 4: Cluster *Z-Scores* for 8 Clusters using *Ward* Method

[41] The 192 countries from Table VII in Appendix H are included and the belonging to a respective cluster is given there in column *8 Clusters*.

Clusters 1, 2 and 3 fluctuate roughly around -0.5 and -1 standard deviations for all variables. Cluster 2, the cluster containing predominantly former USSR/EE countries, deviates from them with a much larger z-score for the variable PAV, i.e. former USSR/EE have a more developed road infrastructure compared to other countries on similar urbanization and income levels. Cluster 3 deviates from these clusters only in the last variable LL, with a larger z-score, hence, all countries grouped in cluster 3 have access to the sea as opposed to those in the former two clusters.
The z-scores for cluster 4 vary roughly around the zero-mean, with larger deviations in the positive direction for the third variable (URB) and the last variable (LL). Hence, those countries in the fourth cluster tend to have larger degrees of urbanization and have access to the sea.
Those four clusters containing the relatively wealthier countries with larger values of urbanization and infrastructure indicating variables, do not fluctuate together as homogeneously as the first three clusters do. The variables of cluster 5 lie in the range between 0 and 1.5 standard deviations. Lower z-scores are observable for the variables PRIM, POPD and EPPC, and this is the only cluster having both, countries with and without access to the sea.
The variables of cluster 6 vary in a similar range to cluster 5, with lower z-scores for variables PAV, RPA and POPD, and a much higher value of EPPC, reaching the highest overall z-score for that variable, a value of 3.36 standard deviations. Table VIII in Appendix I reveals that less densely populated developed countries are contained in this cluster.
Cluster 7's variable values reside in the range of 0.5 to 1.3 standard deviations with major exceptions for the variable RPA, taking the low z-score of -0.051 and the variable PRIM, taking the largest z-score value slightly above 2.
The z-scores of the variables from cluster 8 show major fluctuations on a wide rage from -0.7 to 5.5 standard deviations. This cluster is characterized by the largest z-scores for variables URB, RPA and POPD and the smallest for PRIM. Hence, the countries included in this cluster are densely populated with its populations spread among its respective cities.

Very generally, one could classify the clusters $1-4$ as containing countries having less infrastructure, being less densely populated, on average being less urbanized and being less wealthy, whereas clusters $5-8$ roughly contain countries that are on average wealthier and have a better infrastructure.[42] It is not possible to say that latter cluster group has higher levels of population

[42] *Wealthy* is again referred to the simple meaning of a higher GDP per capita in this context.

density or degrees of urbanization since there is a large fluctuation among these variables.

The 15-clusters solution is achieved via subdividing some clusters obtained from the 8-clusters solution into individual, smaller clusters. The countries included in each one of the 15 clusters are also given in Table VIII in Appendix I. This finer clustering leads to z-scores for the variables of the respective clusters given in Table 3, a plot of the 15-clusters solution is given in Figure 5.

Cluster	**GDP**	**PAV**	**URB**	**RPA**	**PRIM**	**POPD**	**EPPC**	**PHL**	**LL**
1	-0.733	-1.072	-1.177	-0.489	-0.608	-0.329	-0.494	-0.841	-1.914
2	-0.474	0.948	-0.436	-0.378	-0.190	-0.405	-0.223	-0.397	-1.914
3	-0.643	-0.053	-0.913	-0.312	-0.810	0.228	-0.547	-0.750	0.520
4	-0.735	-1.059	-1.127	-0.505	-0.379	-0.507	-0.603	-0.818	0.520
5	-0.569	-0.874	-0.092	-0.450	-0.231	-0.368	-0.502	-0.670	0.520
6	-0.096	-0.028	0.508	-0.395	-0.528	-0.430	-0.007	-0.214	0.520
7	-0.436	0.920	0.489	-0.188	0.674	-0.120	-0.338	-0.333	0.520
8	-0.142	0.169	-0.010	1.229	-0.682	1.321	-0.220	0.218	0.520
9	-0.270	-0.665	0.274	0.001	1.264	-0.069	-0.308	-0.041	0.520
10	1.793	1.254	0.618	0.869	-0.043	0.273	0.182	1.621	-1.914
11	2.014	1.250	1.213	1.675	-0.370	0.632	0.882	1.928	0.520
12	0.773	1.355	0.341	0.117	0.240	-0.270	0.420	1.172	0.520
13	2.097	0.233	1.070	-0.325	0.442	-0.620	3.362	1.990	0.520
14	0.677	0.882	1.268	-0.051	2.059	0.503	0.925	0.593	0.520
15	1.448	1.226	1.666	5.226	-0.713	5.500	1.072	1.578	0.520

Table 2: *Z-Scores* for 15 Clusters obtained by *Ward* Method[43]

Straightforwardly from the subdividing steps of the clustering process follows that z-scores and the corresponding plots for cluster 1 in the 8-clusters framework and cluster 1 in the 15- clusters framework, for clusters 2 and 2, 6 and 13, 7 and 14 and 8 and 15 respectively, are identical, since these clusters represent the same groups of countries in each solution and are not subdivided from the 8-clusters solution to obtain further clusters.

[43]The 192 countries from Table VII in Appendix H are included and the belonging to a respective cluster is given there in column *15 Clusters*.

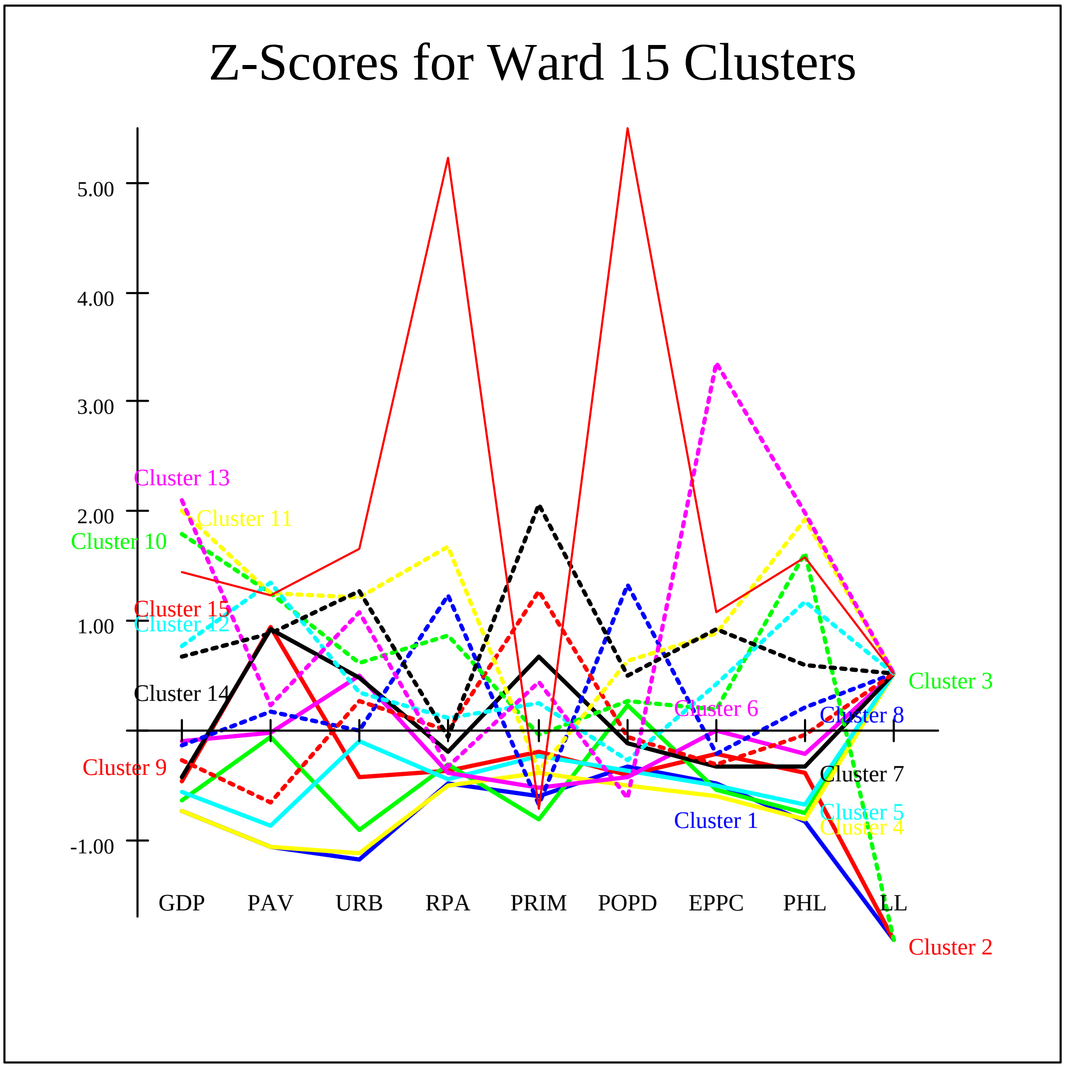

Figure 5: Cluster *Z-Scores* for 15 Clusters using *Ward* Method

The newly obtained cluster 3 in the 15-clusters *Ward* outcome fluctuates between -1 and 0 standard deviations with its variable z-scores with noticeable deviations for variables URB and POPD and access to sea for its countries.
Interesting is that the new cluster 4 almost matches cluster 1 with the only exception of containing those countries with access to the sea.
The z-scores for the respective variables of cluster 5 fluctuate steadily around -0.5 standard deviations with the exception of PAV being slightly lower and URB being slightly higher.
Those new clusters $6-12$ that are obtained from subdividing clusters 4 and 5 from the 8-clusters solution show z-scores fluctuating in the range of -0.5

and 2 standard deviations with specific emphasis on certain variables for each respective cluster.
The plot for the 15-clusters solution, however, reveals numerous overlying lines, most significantly in the range of -0.5 to 1 standard deviations. Hence, a separation of groups of clusters with generally different levels of z-scores, as done for the 8-cluster solution, is not possible anymore. The obtained 15 clusters take very specific forms in which z-scores of the different variables are combined.
More information and interpretation will be possible after having a closer look on the clusters and the countries included in each of them. This will follow in the next subsection.

5.4.2 Descriptive Analysis for *K-Means* Approach

Following the proposal by Hair, Anderson, Tatham & Balck (1998) to combine certain *hierarchical* and *non-hierarchical* clustering algorithms to obtain optimal results, the *K-Means* clustering algorithm is used as a second step to classify the countries according to the prespecified focus. The results obtained from the *Ward* clustering above serve as the starting point, even though the results have already vast explanatory power and reveal interesting findings that will be discussed in more detail in the subsection *A Closer Look at the Clusters*.
The theoretical derivation of the *K-Means* algorithm is presented above. For the computation using the standardized data matrix for the 192 countries, the *Euclidean* distance matrix is used as the distance matrix d, and the results from the *Ward* clustering algorithm are used respectively for the 8-clusters and 15-clusters solutions as the required initial partition. The *XploRe* quantlet utilized for the computation is `g, c, v, s = kmeans(x,t.p,1000)`, where the left-hand-side of the equation are the output parameters, `x` is the data matrix, `t.p` gives the initial partition[44] and `1000` restricts the maximum number of iterations to 1000.
The results obtained from the computation for both numbers of clusters are given in Table IX in Appendix J, where they are directly compared to the clusters derived from the *Ward* procedure. 165 out of the 192 countries, i.e. 86%, belong to the same cluster according to both algorithms in the 8-clusters solution and 163 out of 192, or 85%, do so in the 15-clusters solution. This is a good result indicating that there is a wide-ranging commonality among

[44] This comes from the *Ward* results from above.

the results of both procedures, and the *Ward* algorithm already performed well.
The z-scores for the different variables of the respective clusters from the 8-clusters solution are given in Table 4.

Cluster	GDP	PAV	URB	RPA	PRIM	POPD	EPPC	PHL	LL
1	-0.730	-0.952	-1.201	-0.494	-0.623	-0.345	-0.492	-0.842	-1.914
2	-0.302	0.999	-0.176	-0.216	-0.128	-0.345	-0.101	-0.155	-1.914
3	-0.651	-0.690	-0.728	-0.368	-0.459	-0.158	-0.543	-0.741	0.520
4	-0.193	0.010	0.447	-0.028	0.274	-0.104	-0.152	-0.024	0.520
5	1.889	1.368	0.802	0.936	-0.069	0.393	0.532	1.767	-0.377
6	2.120	0.373	1.076	-0.359	0.534	-0.610	3.552	1.918	0.520
7	0.567	0.871	1.169	-0.075	2.013	0.255	0.639	0.613	0.520
8	1.420	1.205	1.314	4.500	-0.775	4.079	0.862	1.425	0.520

Table 4: *Z-Scores* for 8 Clusters obtained by *K-Means* Method[45]

The graph plotting the z-scores from above for the respective clusters is given in Figure 5. A comparison of the z-score values obtained from the *K-Means* approach and its graphical representation with those obtained from the *Ward* approach reveals what one would already expect given that there is a 86% country-cluster matching among both procedures. The respective cluster z-score-lines look very similar. The most interesting difference is that the range of the overall fluctuations decreases due to the fact that the extremely high z-scores for variables RPA and POPD of cluster 8 from the *Ward* procedure diminish by around 1 standard deviation.
The good resemblance of the two results can be seen in the graphics in Appendix K, where the variable z-scores derived from each one of the two procedures are plotted against each other for every individual cluster. Noticeable, yet minor deviations can only be seen in clusters 4 and 8, however, the overall shape remains for all clusters.

[45]The countries belonging to each cluster are taken from Table IX. The initial partition is the *Ward* clustering from above.

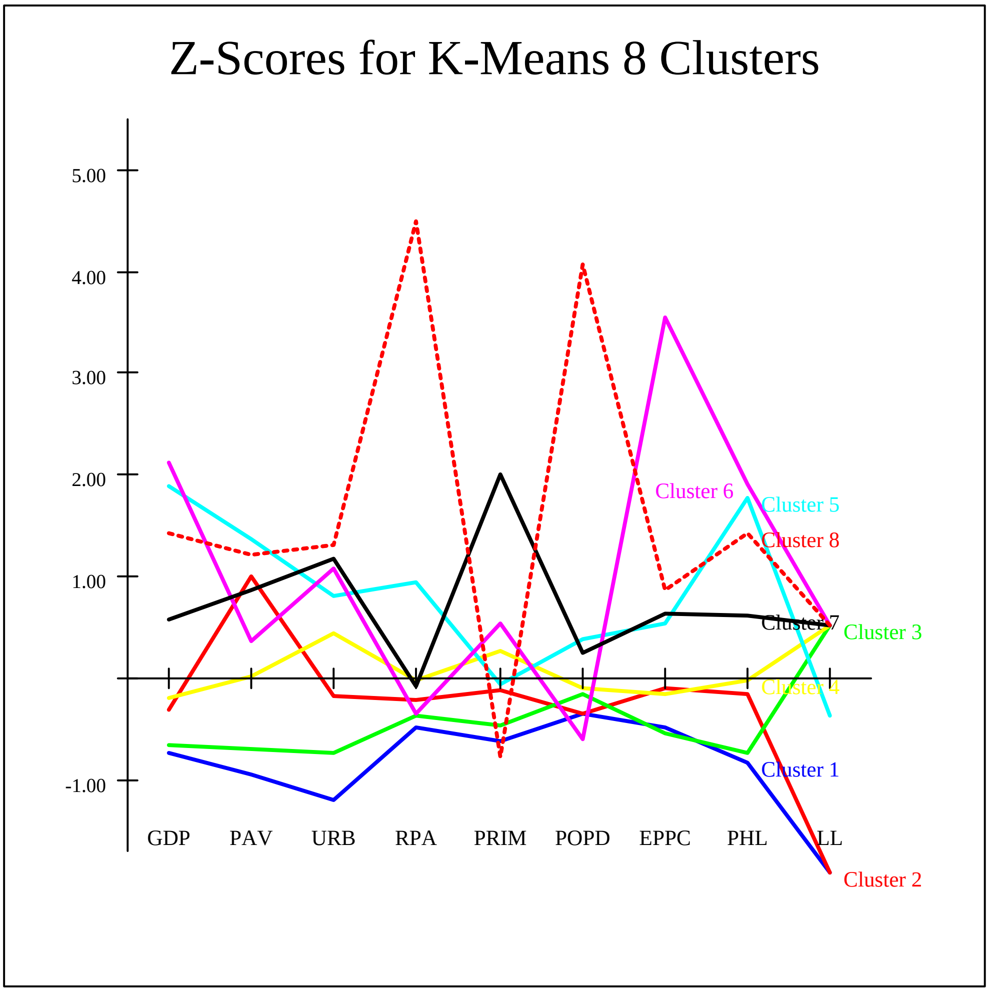

Figure 6: Cluster *Z-Scores* for 8 Clusters using *K-Means* Method

Predefining the number of clusters for the *K-Means* algorithm to 15 yields z-scores for the respective variables as given in Table 5. A separate plotting of the z-scores is left out at this point since the graphs with 15 lines do not show interesting results straightforwardly. A cluster-to-cluster comparison between the *Ward*-result and the *K-Means*-result can rather be observed in Appendix L.

Noticeable deviations occur in clusters 5, 6, 8 and 14, though not altering the general shape of the line and the general level of the z-scores. Cluster 15 has exactly the same z-scores for all 9 variables among derived from both procedures, i.e. the countries grouped in cluster 15 according to each respective algorithm are the same. A result already revealed by Table IX in Appendix J.

Cluster	GDP	PAV	URB	RPA	PRIM	POPD	EPPC	PHL	LL
1	-0.730	-0.952	-1.201	-0.494	-0.623	-0.345	-0.492	-0.841	-1.914
2	-0.364	1.093	-0.226	-0.341	-0.139	-0.365	-0.119	-0.219	-1.914
3	-0.599	0.039	-0.843	-0.188	-0.777	0.241	-0.522	-0.698	0.520
4	-0.733	-0.991	-1.063	-0.508	-0.465	-0.489	-0.607	-0.825	0.520
5	-0.538	-0.896	0.099	-0.427	-0.138	-0.265	-0.492	-0.654	0.520
6	-0.060	0.044	0.639	-0.213	-0.527	-0.314	0.076	-0.063	0.520
7	-0.421	0.923	0.472	-0.143	0.697	-0.125	-0.346	-0.220	0.520
8	-0.192	0.375	-0.027	1.314	-0.395	2.065	-0.322	0.225	0.520
9	-0.200	-0.671	0.239	-0.002	1.574	-0.174	-0.305	0.015	0.520
10	1.969	1.264	0.685	1.009	0.043	0.319	0.139	1.718	-1.914
11	1.914	1.201	1.205	1.515	-0.308	0.779	0.856	1.884	0.520
12	0.783	1.287	0.489	0.154	0.397	-0.111	0.535	1.162	0.520
13	2.120	0.373	1.076	-0.359	0.534	-0.610	3.552	1.918	0.520
14	0.775	0.759	1.338	-0.208	2.535	0.148	1.092	0.452	0.520
15	1.448	1.226	1.666	5.226	-0.713	5.500	1.072	1.578	0.520

Table 5: *Z-Scores* for 15 Clusters obtained by *K-Means* Method[46]

The results obtained from the iterative *K-Means* clustering procedure reveals features stemming from its distinctiveness to the *hierarchical* procedures. As presented before, the *hierarchical Ward* procedure stepwise subdivides its clusters into further sub-clusters. Once an observation has been assigned to a certain cluster, it can only be found in sub-clusters of the initial one in subsequent steps. The *K-Means* approach - as well as any other *non-hierarchical* procedure - allows observations to shift among clusters. Even though cluster 15 matches exactly among both outcomes above, cluster 8 does not so in the 8-clusters solution. The *K-Means* algorithm assigns Belgium to the 8th cluster in the 8-clusters solution, but not to cluster 15 in the second solution, but rather to cluster 11.

5.4.3 Descriptive Analysis for ***Fuzzy C-Means***

The use of a *fuzzy* clustering algorithm differs from those algorithms used above by means of not assigning each observation to one and only one cluster, but rather defining a degree of membership to all clusters based on the values the variables take for each observation. The degree of membership

[46]The countries belonging to each cluster are taken from Table IX. The initial partition is the *Ward* clustering from above.

thus being a value in $[0, 1]$. After obtaining a degree of membership matrix **U** from the iterative *fuzzy C-Means* process (FCM), a *Hard C-Means* approach (HCM) can be used to assign each observation j again to only one cluster, namely the one with the largest value μ_{ij}.[47]
The advantage of fuzzy clustering is that observations to not have to be assigned to only one cluster when original observations are not separated unambiguously. However, depending on the parameters one chooses, observations might not be assigned to one of the proposed clusters at all, because distances to various cluster centroids are the same or too similar. As a third clustering algorithm for cluster analyzing the country data from the perspective of *wealth*, *urbanization* and *infrastructure*, the *Fuzzy C-Means* method, which has been derived technically above, is used in this paper.
Besides prespecifying the number of clusters c, Bezdek[48] discusses the further requirement for prespecification of the terminal condition and a parameter of fuzziness.
The quantlet for *XploRe* used for the computation of the *Fuzzy C-Means* clustering is `fcm = xcfcme(x,c,m,e,alpha)`, where `fcm` is the output giving the membership matrix **U** and the singular cluster for each observation according to maximum degree of membership to one cluster. `x` is the initial data matrix, `c` the prespecified number of clusters, `m` the parameter of fuzziness with $1 < m \leq \infty$, `e` the terminal condition ε and `alpha` the level of the fuzzy set with `alpha` $\in [0, 1]$.
Bezdek (Ruspini, Bonissone & Pedrycz (1998)) states that most authors had good success with a choice of the termination error ε in the interval $[0.01, 0.0001]$. The analysis of the country data will be performed with `e`$= 0.001$.
The choice of the fuzziness parameter m reveals a major problem for the analysis of the underlying data set. Bezdek and other authors point out that m ranges in most research between $[1.1, 5]$ with $m = 2$ being an overwhelming favorite. When applying this value with the above defined ε and a standard value of `alpha` $= 0.9$ for computation of 8 clusters out of the data set, a reasonable partition matrix **U** is obtained, given in Appendix M, but every observation is assigned to cluster 9, i.e. an additional cluster. An additional cluster is created when degrees of membership for one observation do not differ too much for several clusters. In the benchmark case, the distance of

[47] The notation is given in section 4.4.3.

[48] J. C. Bezdek was the one who developed the *Fuzzy C-Means* algorithm in 1981 based on the introduction of fuzzy sets by L. A. Zadeh in 1965 and the *Hard C-Means* algorithms developed by Ruspini (1969). The discussion of fuzzy clustering in this section follows the article by J. C. Bezdek: *Fuzzy Clustering*, published in Ruspini, Bonissone & Pedrycz (1998), pp. F6.2:1 ff.

an observation to two cluster centers is equal. But even a distance which is not exactly equal but close, results in difficulties to assign one country to a specific cluster. Reason for this outcome is the defined fuzziness parameter, which is not applicable to the data. There is no clear and obvious separation of the country data that can be detected by rough procedures. Instead, rather subtle devices have to be used to detect the less pronounced cluster limits underlying the country data set.
This reveals special characteristics of the data underlying the analysis of this paper. The countries of the world are too different from each other to be clearly and straightforwardly grouped in subgroups. If one wants to do so - and the results from the *Ward* and *K-Means* procedures gave good reasons to do so - one has to adjust the algorithm to obtain satisfying results. For this reason I deviated from the suggested values for m and performed the computation with a lower value of fuzziness, $m = 1.01$. For the computation with this parameter, the software assigned each observation to a reasonable cluster out of clusters 1 to 8. However, non of the derived clusters from the fuzzy computation, neither the cluster i assigned to each observation from hardening the $c - means$, nor the cluster with the largest value for μ_{ij} are close to being as satisfying as the results obtained from the *Ward* clustering and the *K-Means* clustering. A matching coefficient for those observations that fall into the same cluster according to all three procedures or according to the fuzzy clustering plus one of the others is much lower than those 85% or 86% obtained before. And that is not due to the fact that clusters have to be renumbered after the *Fuzzy C-Means* clustering because it is a *non-hierarchical* clustering algorithm without initial partition. Hence, cluster numbers are assigned randomly.

Given that using the *Fuzzy C-Means* clustering algorithm on the data set of interest does not deliver satisfying results, and given that the result obtained from *Ward* and *K-Means* clustering are, in fact, satisfying and consistent, latter two should suffice to define the clusters in this analysis and interpret them over and above the descriptive analysis.

5.5 A Closer Look at the Clusters

Besides looking at the z-scores of the variables of each cluster describing it, a closer look at the countries actually included in each of them reveals important information and a background for interpretation. Combining this information with the z-scores of the respective clusters, leads back to the

core interest of analysis of this paper, how the countries of the world can be clustered into sub-groups, what countries belong to the respective groups and why they do so. Description and interpretation of the resulting clusters should answer these questions.
This part of the analysis will mainly focus on the result for the 8-clusters solution obtained from the *K-Means* clustering algorithm. The 8-clusters solution provides a more useful framework for practical use of the results from this empirical investigation, since it is easier to address a smaller number of clusters with common features. And the obtained 8 clusters serve as a good basis for interpretation.
Utilizing the result of the *K-Means* algorithm is a consequence of the aforementioned proposal by Hair, Anderson, Tatham & Balck (1998) to combine *hierarchical* and *non-hierarchical* procedures. Moreover, the results obtain from the *Ward* clustering are embedded in the *K-Means* solution as explained above.

Cluster 1

Cluster 1 contains the following countries:

Category (# of Countries)	**Countries**
LLDCs (15)	Afghanistan, Bhutan, Burkina Faso, Burundi, Central African Republic, Chad, Ethiopia, Lao People's Dem. Rep., Lesotho, Malawi, Mali, Nepal, Niger, Rwanda, Uganda
LDCs (4)	Bolivia, Mongolia, Paraguay, Swaziland
Others (2)	Zambia, Zimbabwe

Table 6: Countries in Cluster 1 (Obtained from *K-Means* 8-Clusters Solution)

Cluster 1 had the lowest z-scores for all variables except for PRIM, POPD and EPPC. But even for these variables, its z-scores reside close to the minima. Hence, these countries can be considered as the poorest and least developed of the world. All variables that express well-being and those, that add to or develop well-being reach only low levels. In addition, all countries in this cluster are landlocked. Investment into all sort of infrastructure is utmost required in these countries and levels of urbanization should be increased to achieve positive external effects.

Cluster 2

Category (# of Countries)	**Countries**
LLDCs (1)	Botswana
USSR/EE (12)	Armenia, Azerbaijan, Belarus, Hungary (also OECD), Kazakhstan, Kyrgyzstan, Republic of Moldova, Slovakia (also OECD), Tajikistan, The FYR of Macedonia, Turkmenistan, Uzbekistan

Table 7: Countries in Cluster 2 (Obtained from *K-Means* 8-Clusters Solution)

Striking for this cluster is the fact that transition economies of the former USSR and Eastern Europe are very well isolated into this cluster. Merely Botswana is also assigned to this cluster. Interestingly, Hungary and Slovakia are moved from cluster 5 from the *Ward* procedure into this cluster by the *K-Means* algorithm. Both being candidate countries for accession into the European Union.
Cluster 2 has higher z-scores than the former cluster for all variables. Especially the variable PAV reaches a high value of almost 1 standard deviation. This stems from the infrastructure investment during the USSR era. However, the countries included in cluster 2 show low levels of GPD and are neither very densely populated nor very urbanized. All countries from this cluster are also landlocked.
It remains uncertain if the high levels of PAV still truely reflect good infrastructure since the state of the road pavement in these countries is not addressed. It might be that lower levels of GDP kept these countries from maintaining the roads.

Cluster 3

With 59 countries, cluster 3 is the largest cluster. Both, LLDCs and LDCs are represented in this cluster in high frequency. Surprising is the presence of South Africa.
This cluster is characterized by similarly low z-score values for all variables to cluster 1. Except for minor positive deviations for some variables, the only big difference is that all countries have access to the sea. Otherwise, the same policy conclusions as for cluster 1 hold.

Category (# of Countries)	**Countries**
LLDCs (20)	Bangladesh, Benin, Comoros, Equatorial Guinea, Eritrea, Gambia, Guinea, Guinea-Bissau, Haiti, Mauritania, Mozambique, Myanmar, Samoa, Sierra Leone, Somalia, Sudan, Togo, United Rep. of Tanzania, Vanuatu, Yemen
LDCs (36)	Algeria, Angola, Belize, Cambodia, Cameroon, China, Congo, Republic, Cte d'Ivoire, Dem. Republic of Congo, Ecuador, French Polynesia, Ghana, Guatemala, Guyana, Honduras, India, Indonesia, Kenya, Korea, Dem. People's Rep. of, Liberia, Madagascar, Micronesia, Fed. States of, Morocco, Namibia, Nicaragua, Nigeria, Pakistan, Papua New Guinea, Philippines, Senegal, Solomon Islands, Sri Lanka, Syrian Arab Republic, Thailand, Tonga, Vietnam
USSR/EE (2)	Albania, Bosnia and Herzegovina
Others (1)	South Africa

Table 8: Countries in Cluster 3 (Obtained from *K-Means* 8-Clusters Solution)

Cluster 4

Cluster 4 is the second largest cluster, comprising 53 countries. These are mainly LDCs, some LLDCs, and the more developed ones of the USSR/EE countries. Four out of the eight USSR/EE economies willing to become members of the EU in the first round of eastern enlargement belong to this cluster.
The z-scores for all variables are higher than those for clusters 1 and 3, in fact, they fluctuate between those of cluster 1 and 3 and those of clusters 5 and 7.[49] A high z-score is especially reached for the variable URB, indicating that the countries in this cluster tend to have larger degrees of urbanization than those countries in former clusters. Again, all countries from cluster 4

[49]Similar to cluster 2 in comparison to clusters 1 and 3, cluster 6 escapes from the more common pattern of clusters 5 and 7.

have access to the sea.

Category (# of Countries)	**Countries**
LLDCs (4)	Cape Verde, Djibouti, Sao Tome and Principe, Tuvalu
LDCs (36)	Antigua and Barbuda, Argentina, Brazil, Brunei Darussalam, Chile, Colombia, Costa Rica, Cuba, Dominica, Dominican Republic, Egypt, El Salvador, Fiji, French Guyana, Gabon, Grenada, Guadeloupe, Iran (Islamic Rep. of), Iraq, Jamaica, Jordan, Libyan Arab Jamahiriya, Malaysia, Mauritius, Oman, Panama, Peru, Reunion, Saint Kitts and Nevis, Saint Lucia, Saint Vincent / Grenadines, Saudi Arabia, Suriname, Trinidad and Tobago, Tunisia, Venezuela
USSR/EE (10)	Bulgaria, Croatia, Estonia, Georgia, Latvia, Lithuania, Poland (also OECD), Romania, Russian Federation, Ukraine
OECD (2)	Mexico, Turkey
Others (1)	Yugoslavia

Table 9: Countries in Cluster 4 (Obtained from *K-Means* 8-Clusters Solution)

Very interestingly, this cluster still contains countries classified as LLDCs, even though, OECD countries are included at the same time. This cluster heavily questions the UN classification of Cape Verde, Djibouti, Sao Tome and Principe and Tuvalu being LLDCs and therefore receiving preferential treatment over other LDCs assigned to lower clusters by this analysis.

On the other hand, it reveals that two countries being members of the OECD, namely Mexico and Turkey, reach only lower levels of well-being and development.[50]

[50]Development is used in the context of the analysis of this section to address those variables from the categories *urbanization* and *infrastructure* that contribute to well-being as derived in the initial section of the motivation for the analysis.

Cluster 5

Category (# of Countries)	**Countries**
USSR/EE (2)	Czech Republic (also OECD), Slovenia
OECD (14)	Austria, Denmark, France, Germany, Greece, Ireland, Italy, Japan, Luxembourg, Korea, Republic of, Netherlands, Spain, Switzerland, United Kingdom
Others (3)	Andorra, Liechtenstein, San Marino

Table 10: Countries in Cluster 5 (Obtained from *K-Means* 8-Clusters Solution)

Cluster 5 is evidently the cluster containing a large share of OECD countries, especially those located in Europe. The z-scores for all variables take on average higher values in comparison to clusters 1 to 4. The variable PAV takes the highest average value in this cluster and the variables GDP, RPA, POPD and PHL take the second highest values of the overall z-scores from the entire sample. Merely the variable PRIM takes a z-score value close to the overall sample mean and is thus lower than that of other clusters.
The two EU enlargement candidates Slovenia and the Czech Republic are contained in this cluster and therefore reveal most commonalities with countries already being part of the EU as compared to other countries of the world.
Cluster 5 shows one unique characteristic in that it is the only cluster comprising landlocked countries as well as countries with access to the sea. Hence, it can be concluded that values for all other variables are so similar that they outweigh the impact of having a different value for the binary variable LL.

Cluster 6

This cluster is smaller than the clusters before, it contains only eight countries. Seven of those are OECD economies, while one, the United Arab Emirates, is classified as a LDC. Interpreting the OECD economies contained in this cluster rather than in cluster 5 leads to the conclusion that cluster 6 contains those non-European and Scandinavian OECD economies, which have similar (although on average slightly higher) values for those variables revealing well-being while especially population density and connected to that, RPA take lower values. Moreover, the countries in this cluster are bigger oil producers than those from cluster 5, which results in a larger z-score value for EPPC.

Category (# of Countries)	**Countries**
LDCs (1)	United Arab Emirates
OECD (7)	Australia, Canada, Finland, Iceland, Norway, Sweden, United States of America

Table 11: Countries in Cluster 6 (Obtained from *K-Means* 8-Clusters Solution)

The question, why the United Arab Emirates are still considered as a LDC evidently arises from this result. Its characteristics based on the values for the variables taken into account for the analysis of this paper and for describing its state of *wealth*, *urbanization* and *infrastructure*, show greatest similarities to those countries recognized as the most developed on the world.

Cluster 7

The countries in cluster 7 show features not being in line with those of clusters 5 and 6. Z-scores for variables GDP and EPPC are much lower than those for clusters 5 and 6, whereas PRIM reaches the by far largest value and URB takes the second largest value among the 8 clusters. Having a look at the countries reveals that all countries have rather small area surfaces (possibly with the exception of New Zealand), but each does have one major metropolis, generating the large z-score for PRIM. Some countries are even island states. These countries, however, do not reach development levels close to those of the former two clusters.[51] This is the reason for the predominance of LDCs in this cluster.

[51] In this case, *development levels* refers again primarily to those variables representing well-being as given in GDP per capita, and those reflecting good infrastructure.

Category (# of Countries)	**Countries**
LDCs (11)	Bahamas, Kuwait, Lebanon, Nauru, Netherlands Antilles, New Caledonia, Palau, Puerto Rico, Qatar, Seychelles, Uruguay
OECD (2)	New Zealand, Portugal
Others (1)	Israel

Table 12: Countries in Cluster 7 (Obtained from *K-Means* 8-Clusters Solution)

Comparison of the outcome from the *K-Means* and the *Ward* clustering reveals again some mismatches worth to note. The Seychelles and Uruguay where grouped into cluster 4 according to the *Ward* procedure, while Portugal was assigned to cluster 5 and New Zealand to cluster 6. In this case, interpretation might have been somewhat easier with the *Ward* results since Uruguay is a Latin American LDC, Portugal a EU country and New Zealand a less densely populated non-European OECD member. Nevertheless, interpretability is also given with the *K-Means* result and these specific mismatches reveal new similarities between these countries contained in cluster 7 according to the *K-Means* algorithm.

Cluster 8

Cluster 8 is the smallest cluster consisting of only five countries. Members of this cluster are on average even smaller than those in cluster 7. Three out of the five countries are island states, Qatar is a small enclave, a peninsula in the Persian Gulf. Only Belgium is a slightly larger country and surprisingly resides in this cluster. It is worth noting that the *Ward* algorithm assigned only Bahrain, Bermuda and Malta into this cluster, while grouping Barbados to cluster 4 and Belgium into cluster 5 with the majority of other EU members. The same corresponding criticism as for cluster 7 holds.
This cluster is characterized by major variance of the different z-scores. Variables RPA and POPD take extremely high values, at the same time, cluster 8 has the lowest z-score for the variable PRIM. Variables describing wealth and good infrastructure, mainly GDP, EPPC and PHL, are among those three clusters with the highest z-scores, hence those countries in this cluster can be described as being well developed. Bahrain and Barbados being LDCs sets forth renewal for criticism of this categorization.

Category (# of Countries)	**Countries**
LDCs (2)	Bahrain, Barbados
OECD (1)	Belgium
Others (2)	Bermuda, Malta

Table 13: Countries in Cluster 8 (Obtained from *K-Means* 8-Clusters Solution)

Looking at the z-scores of the variables for the distinctive clusters provides a good framework for interpretation of the different resulting clusters as done above. The main conclusions are that the differentiation between LLDCs and LDCs is unjustified if one focuses on the categories *wealth*, *urbanization* and *infrastructure* and the specific analysis of this paper is performed,[52] that EU accession candidates are assigned to very different clusters, and that the obtained clusters allow for systematic policy conclusions based on the specific characteristics of each cluster.
These conclusions will be discussed in the final section *Summary and Conclusion.*

5.6 Analysis of 8-Clusters Solution Omitting *Landlocked*

The analysis provided in the subsection above provides a good solution to the key question underlying this thesis. One questions remains adherent to the computation before. The variable *landlocked* is the only binary variable and could therefore have too much of a separate influence, i.e. drive the clustering process towards grouping countries with the same values of *LL*. Hence, it is of interest to find out if an analysis omitting this variable would deliver entirely different results.
I performed the cluster analysis with the same data set using the remaining 8 variables except *LL*. The results for the algorithm of major interest - the 8-Clusters *K-Means* solution - is given in Table XII in Appendix N, with a graph of the z-scores in Appendix O.
Evidently, this clustering process delivers different results than the ones before. However, these results are not strongly in contrast to the findings before.

[52]It should be mentioned again that those three categories are the key components for explaining well-being and development of different countries, as motivated from growth theory. Thus, results based on computation with variables quantifying these categories have momentous explanatory power.

The newly obtained Cluster 1 comprises most of those countries that were formerly grouped in Clusters 1 and 3 and is by far the largest cluster containing 62 countries. The magnitude of this cluster reveals problems with finding smaller groups of countries within the entity. But the finding remains that *LLDC*s and *LDC*s are both contained in this cluster without predominance of one of them. Hence, this classification of developing countries cannot be supported by the analysis of this paper.
This new clustering procdure does not separate the landlocked transition economies of the former USSR and Eastern Europe as consistently as the one including the variable *LL* does.
The outcome of the analysis without the variable *landlocked* sets forth new questions considering individual countries. Especially the classification of Bangladesh, Djibouti, Gambia and Tuvalu as *LLDC*s is questionable according to the results from the analysis as these countries appear in clusters with variable values indicating higher degrees of development.
Greece and Portugal being in Cluster 3 and Mexico and Turkey being in Cluster 4 shows again differences among EU and OECD economies as found out in the analysis above.
Concluding this separate cluster analysis omitting the variable *landlocked* reveals that this variable indeed has a strong impact on the clustering outcome and delivers somewhat different results. The key findings of the analysis including this variable are not contradicted. Key classifications of countries are robust.
Since the explanatory power for economic development of the variable *landlocked* is large and access to the sea is important for a country not only, but especially for economic reasons, an inclusion of this variable into the analysis is well justified. However, one should be aware of the effect this inclusion has on the results and compare them.

6 Factor Analysis

Having obtained the clusters and giving interpretation for these, one question concerning the underlying data set and analysis remains of interest. What variables or combinations of variables influenced the specific clustering the most? That is, are there variables that fluctuate more and thus add more to separate observations or countries from one another than others.
Various statistical methods tackle this question by trying to extract *principal components*, *factors* or others to determine key influential variables or com-

binations that have most explanatory power for a given data set. *Principal Component Analysis*, *Factor Analysis* and others are the techniques aimed at isolating the parameters of influence. Theoretical derivation of the different techniques as well as their discussion will be omitted at this point. Detailed information can be found in Johnson & Wichern (1998), Härdle & Simar (2002) and other sources.
One aim of these methods is the reduction of dimensionality, same as it is for the cluster analysis. Nevertheless, the way towards reducing dimensions and the results and explanatory context of the techniques varies substantially.

6.1 Theoretical Derivation

In order to target the question what variables or sets of variables are mainly responsible for the clustering obtained from the cluster analysis, this section will give a factor analysis of the country data, since this technique is regarded as being more elaborate[53] than principal component analysis and serves the purpose of detecting unobservable *factors* underlying the structure of the data set. Since the key answers for the initial purpose of research of this paper - namely a sub-grouping of the countries of the world according to a prespecified focus - are answered in the section *Cluster Analysis*, this section should give some additional information and is thus kept short.

The factor model assumes that an observable, p-dimensional random vector $\mathbf{X}$ can be described as a linear combination of a few random variables $F_1, F_2, ..., F_m$ called *common factors* and p *specific* error terms. The model can thus be written as

$$\mathbf{X} - \mu = \mathbf{LF} + \varepsilon \tag{27}$$

where $\mathbf{X} - \mu$ is the mean subtracted p-dimensional observable random vector, $\mathbf{L}$ a $p \times m$ matrix of *factor loadings*, $\mathbf{F}$ an $m \times 1$ vector of *common factors* and ε the p-dimensional vector of *specific* variations, with $m < p$. In this model, p variables of the random vector $\mathbf{X}$ can be explained by a smaller number of factors m. Respectively, the coefficient l_{kj} of the matrix $\mathbf{L}$ is the *loading* of the kth variable on factor j.[54]
With the resulting unobservable $m+p$ random variables $F_1, F_2, ..., F_m, \varepsilon_1, \varepsilon_2, ..., \varepsilon_p$ a direct verification of the model from the observations in $\mathbf{X}$ is hopeless.

[53] Compare Johnson & Wichern (1998) for remarks on this.
[54] The notation is taken from Johnson & Wichern (1998), but again adapted to the notation of this paper.

Hence, assumptions on the variance-covariance structure of the random variables have to be made in order to make the model possible to be estimated. These assumptions are

$$E(\mathbf{F}) = \mathbf{0}, \quad Cov(\mathbf{F}) = \mathbf{I} \tag{28}$$

$$E(\varepsilon) = \mathbf{0}, \quad Cov(\varepsilon) = \psi, where\ \psi\ is\ a\ diagonal\ matrix \tag{29}$$

and $\mathbf{F}$ and ε are independent

$$Cov(\varepsilon, \mathbf{F}) = \mathbf{0}. \tag{30}$$

The model from above together with the assumptions leads to the *orthogonal factor model.*
For estimation purposes, the portion of the variance of each variable X_k explained by the m common factors is of interest and called the *communality.* This is denoted by h_k^2. As a result, the overall variance σ_{kk} can be decomposed into the *commonality* $h_k^2 = l_{k1}^2 + l_{k2}^2 + ... + l_{km}^2$ and the *specific variance* ψ_k:

$$\sigma_{kk} = l_{k1}^2 + l_{k2}^2 + ... + l_{km}^2 + \psi_k. \tag{31}$$

Straightforward computation from the factor model leads to the following covariance structure of the *orthogonal factor model*

$$Cov(\mathbf{X}) = \mathbf{LL}' + \psi \tag{32}$$

where $Var(X_k = l_{k1}^2 + l_{k2}^2 + ... + l_{km}^2 + \psi_k$ and $Cov(X_k, X_l) = l_{k1}l_{l1} + ... + l_{km}l_{lm}$. The task of factor analysis is to find combinations of *common factors* and their *loading coefficients* that represent the covariance structure in an adequate way.

Again, there are various solutions to the model, among which the most commonly used are the *principal component* solution, the *principal factor* solution and the *maximum likelihood* solution. If the factors are chosen appropriately, all solutions should be consistent. Therefore, a theoretical background for the *principal component* solution should suffice at this stage.[55]
Spectral decomposition of the covariance matrix $\mathbf{\Sigma}$ of the underlying data set $\mathbf{X}$ allows us to rewrite $\mathbf{\Sigma}$ as

$$\mathbf{\Sigma} = \lambda_1 \mathbf{e}_1 \mathbf{e}_1' + \lambda_2 \mathbf{e}_2 \mathbf{e}_2' + ... + \lambda_p \mathbf{e}_p \mathbf{e}_p' \tag{33}$$

[55] For a detailed discussion of various solutions to the factor model consult Johnson & Wichern (1998).

$$= [\sqrt{\lambda_1}\mathbf{e}_1 \ \sqrt{\lambda_2}\mathbf{e}_2 \ ... \ \sqrt{\lambda_p}\mathbf{e}_p] \begin{bmatrix} \sqrt{\lambda_1}\mathbf{e}_1 \\ \sqrt{\lambda_2}\mathbf{e}_2 \\ ... \\ \sqrt{\lambda_p}\mathbf{e}_p \end{bmatrix} \tag{34}$$

where $\lambda_1 \geq \lambda_2 \geq ...\lambda_p \geq 0$ are the sorted eigenvalues of the covariance matrix and the $\mathbf{e}_i$s the corresponding eigenvectors. If some eigenvalues $\lambda_{m+1}, \lambda_{m+2}, ...\lambda_p$ are very small or equal to zero, the corresponding pairs of eigenvalues and eigenvectors can be left out for the approximation of $\mathbf{\Sigma}$. The matrix of estimated factor loadings can then be given as

$$\tilde{\mathbf{L}} = [\sqrt{\hat{\lambda}_1}\tilde{\mathbf{e}}_1 \ \sqrt{\hat{\lambda}_2}\tilde{\mathbf{e}}_2 \ ... \ \sqrt{\hat{\lambda}_m}\tilde{\mathbf{e}}_m] \tag{35}$$

and the specific variances ψ_k are given by the diagonal elements of the matrix $\mathbf{S} - \tilde{\mathbf{L}}\tilde{\mathbf{L}}'$, where $\mathbf{S}$ is the sample covariance matrix.[56]

6.2 Empirical Analysis

For the empirical computation of the *factor model* for the underlying set of data for the countries of the world, the *XploRe* quantlet
`b=factoranalysis(x,3,"PCM",10)` is used, where `b` is the vector of outputs containing the matrix of factor loadings, the proportion of the explained variance of the jth factor, the vector of estimated commonalities and the vector of estimated specific variances, `x` is the original (in this cased standardized) data matrix, 3 the prespecified number of factors m, `"PCM"` defines the method being used to derive the factors - in this case the *principal components method* - and 10 is the number of maximal iterations.[57]
Computation leads to the following results

[56]This theoretical derivation of the factor analysis and the factor model is rather short and omitting some specifics and attention to be paid. Especially the topic of non-uniqueness of factor loadings needs to be addressed. Further, various solutions to the model exist. Hence, this section should be regarded as a short overview of the specific analysis. Further discussion can be found in Härdle & Simar (2002) or Johnson & Wichern (1998). The following empirical computation will consider these specificities and dangers. Therefore, the results that are given should be regarded as being theoretically profound.

[57]A value of 10 is recommended and sufficient.

Variable	$\tilde{l}_{k1}$	$\tilde{l}_{k2}$	$\tilde{l}_{k3}$	$\tilde{h}_k^2$	ψ_k
GDP	0.9016	0.0745	-0.2335	0.8729	0.1271
PAV	0.6990	-0.0903	-0.2723	0.5710	0.4290
URB	0.7707	0.3081	0.2068	0.7316	0.2684
RPA	0.6487	-0.6567	0.1753	0.8828	0.1172
PRIM	0.2987	0.6144	0.3185	0.5681	0.4319
POPD	0.4533	-0.7403	0.3301	0.8624	0.1376
EPPC	0.7105	0.3768	-0.1594	0.6722	0.3278
PHL	0.9182	0.0354	-0.1764	0.8755	0.1245
LL	0.1903	0.1915	0.8313	0.7640	0.2360

Table 14: Factor Loadings

The first three factors account for 75.56% of the overall variance. That is a good result, which could be improved by adding more factors into the analysis, but interpretability of additional factors would be difficult. Hence, this analysis utilizes the first three factors only.

A look at the factor loadings and the graphic in Figure 6 allows interpretation of the three factors.[58]

[58] A *varimax* rotation is used on the data to improve the graphical interpretation. The *varimax criterion* is used to find the optimal angle between the factor loadings that maximizes the sum of the variances of the squared loadings. A detailed discussion can be found in Härdle & Simar (2002).

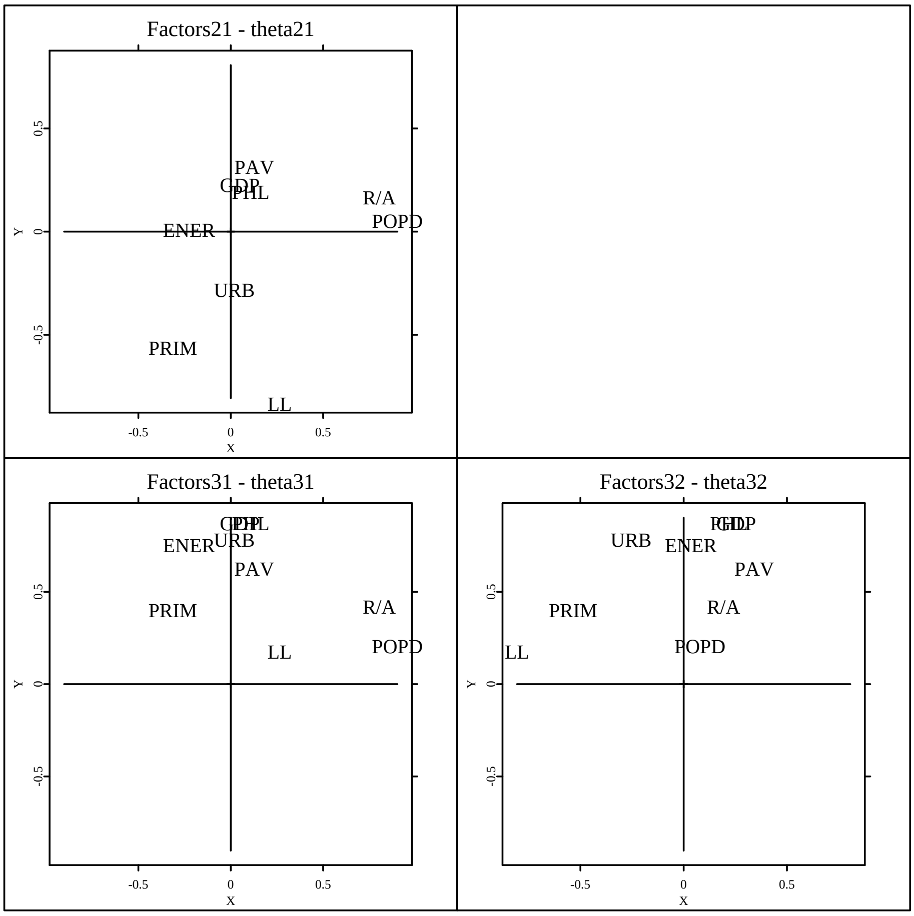

Figure 7: Plot of Pairs of Factors

First factor loadings are most emphasized for variables GDP and PHL. Hence, this first factor can be regarded as some kind of a *wealth*, or *well-being* factor that distinguishes countries according to these variables.
The second factor is mostly driven by the variables RPA and POPD. This gives rise for interpreting the second factor as a factor indicating how densely a country is populated and thus requires more density of roads.
The third factor is predominantly influenced by the variable LL. Therefore, it can be regarded as a geographic factor distinguishing the countries between landlocked and non-landlocked.
This interpretation of the factors can be supported by a look at the correlation structure of the variables, which has not been done throughout the paper so far. The correlation matrix $\mathbf{P}$ of the country data set is the following[59]

[59]This is the correlation matrix of the standardized data.

Var.	GDP	PAV	URB	RPA	PRIM	POPD	EPPC	PHL	LL
GDP	1.000	0.569	0.627	0.497	0.166	0.236	0.698	0.910	0.050
PAV	0.569	1.000	0.455	0.379	0.112	0.288	0.368	0.617	-0.041
URB	0.627	0.455	1.000	0.326	0.439	0.187	0.529	0.618	0.286
RPA	0.497	0.379	0.326	1.000	-0.074	0.789	0.180	0.545	0.081
PRIM	0.166	0.112	0.439	-0.074	1.000	-0.093	0.264	0.213	0.184
POPD	0.236	0.288	0.187	0.789	-0.093	1.000	0.042	0.287	0.116
EPPC	0.698	0.368	0.529	0.180	0.264	0.042	1.000	0.646	0.136
PHL	0.910	0.617	0.618	0.545	0.213	0.287	0.646	1.000	0.084
LL	0.050	-0.041	0.286	0.081	0.184	0.116	0.136	0.084	1.000

Table 15: Correlation Matrix of the Standardized Data

The correlation matrix reveals that GDP and PHL are highly correlated, hence, these two variables are indeed an indicator of *well-being*. The correlation between RPA and POPD is not as high, but still the largest correlation for these two variables. This gives an explanation for the two variables explaining one factor.
The variable LL shows that it is almost uncorrelated with most of the data, explaining why it makes up a factor of its own.

As a conclusion, the resulting three factors account for a reasonably large portion of the overall variance and explain to a good extent, which underlying but unobservable factors are responsible for the specific clusters obtained throughout the analysis.

7 Summary and Conclusion

Can there be a more subtle grouping of the countries of the world according to development standards, or is the currently most frequently used division into least developed, less developed and developed countries already the best approach towards explaining differences among groups of countries in the world? This was the initial question this paper set forth and the research was aimed at.

There are a variety of influential variables for economic and social development and well-being. Since development occurs continuously on a time-path, these variables of development are motivated from growth theory. Wide-ranging research has been done on the field of economic growth, detecting a variety of variables and parameters of interest. These range from demographic to geographic to infrastructure to health to educational to political variables. However, it is difficult to quantify some of these variables objectively, especially geographical variables and those determining political stability.

The analysis of this paper is restricted to the focus on *wealth*, to determine well-being, *urbanization* and *infrastructure*. Variables from these categories are objectively quantifyable, allowing sound statistical results. Moreover, these variables explain social and economic development well and thus are helpful to achieve good results for the purpose of the research of this paper. In addition, basing the results of the analysis on these variables, makes policy conclusions applicable, since changing infrastructure and demographic patterns in a country can be easier than changing political structure, let alone geographic structures.

However, throughout the entire analysis it should be kept in mind, that the analysis is restricted to certain variables from these categories and therefore a limited picture of the real world - yet a very useful and powerful one.

The statistical methodology *cluster analysis* is the appropriate tool to group observations, in this case the countries of the world, with most similarities into common clusters, without the need for prior specifications. Hence, *cluster analysis* is the core technique used in this paper to obtain the desired groups of countries over and above the classification into LLDCs, LDCs and developed countries. The appropriate choices of distance measures and clustering algorithms for the analysis have been derived in detail and used in the empirical computation.

Based on the outcome of different quantities of clusters and the interpretability of the obtained clusters with respect to the question of interest of this paper - namely a clustering of the countries of the world with the focus on

wealth, *urbanization* and *infrastructure* allowing for policy conclusions -, the decision was to consider an 8-clusters solution and a 15-clusters solution, with more in-depth analysis of the former due to better interpretability and less for the latter.
A closer look at the obtained 8 clusters revealed that a classification of the countries going further than the partition into LLDCs, LDCs and developed countries is justified and gives ground for useful findings.
The division into LLDCs and LDCs is mainly based on the level of GDP in each country. Including more variables into a classification, in this case infrastructure and demographic variables, shows no consistency with these results. Countries categorized as LLDCs appear in many clusters mixed with LDCs, without a clear pattern of distinct appearance. In non of the obtained clusters, only LLDCs or only LDCs are present. Moreover, if considering a category such as *developing countries*,[60] clearer borders should be set to define levels until which countries should be categorized as such. The solution of the cluster analysis revealed that some LDC countries reside in clusters with high levels of GDP and good infrastructure, dominated by OECD countries.
Two other interesting findings are that most transition economies of the former USSR and Eastern Europe appear to have common patterns which allow them to be separated from other countries according to their characteristics. The other finding is that candidate countries for EU accession seem to be diverse when considering *wealth*-, *urbanization* and *infrastructure*-variables. Some are close to development levels of the countries already being EU members - the Czech Republic and Slovenia -, while others find themselves being on lower levels of development sharing clusters with *developing countries*.

The obtained 8 clusters allow for a more detailed description of the countries comprised in them with connected policy conclusions to enhance development especially in the clusters with lower levels of development.
Cluster 1 and 3 contain those countries which are least developed according to demographic and infrastructure indicators. These countries need special support to improve their infrastructure, i.e. road investment, road improvement as well as information infrastructure, on a broad scale. Further, rural development needs to be pushed, while at the same time the development of larger urban centers should be supported to allow for positive spillovers. If one wants to call a group of countries least developed, one should call it the

[60] *Developing countries* here refers to those countries classified as LLDCs and LDCs.

countries contained in these two clusters.[61]
Cluster 2 contained mostly landlocked countries of the former USSR and Eastern Europe. These countries also need further support to improve the infrastructure, in this case predominantly to improve the already existing but decaying infrastructure. Further sources to accelerate economic growth in countries contained in this cluster must also be found outside the proposals of this paper.
Countries of cluster 4 also need broad scale support to improve their infrastructure and demographic patterns to advance faster, yet they do not reside on such low levels as the former countries do. While road infrastructure variables take comparably higher values, these countries lack on EPPC and PHL. Hence, support to improve provision with these sources of economic growth is most important. If one wanted to call the countries contained in clusters 1 and 3 *least developed countries*, the countries of cluster 4 would be apt to be called *less developed countries* as a conclusion of the analysis of this paper. However, this broad classification has been criticized throughout the paper.
Clusters 5 and 6 contain the majority of the so-called industrialized, OECD countries. These countries show comparably high values for all variables with those countries in cluster 6 having remarkably high values of EPPC due to the fact that a lot of these countries are important oil producers. Countries grouped in these two clusters do not need support, but should rather set free forces to enhance development in other countries.
Mainly small countries and island states are grouped in cluster 7, which also reveals high levels of variable values. Hence, these countries do not need specific aid, even though many of them are classified as LDCs. Island states have given and unalterable disadvantages due to their geographic situation when it comes to trade of goods. The status of being an LDC is questionable for most countries in this cluster.
Cluster 8 is a special, outlying cluster. Its variable values do not show a consistent pattern, since z-scores for the different variables fluctuate on a broad scale. The cluster comprises LDCs as well as OECD countries, with high variable values on average for infrastructure as well as demographic variables. Merely the z-score for PRIM is the lowest. However, this is not the most important source for economic development, hence the countries from this cluster are not those that require support the most. Again, Bahrain and Barbados being categorized as LDCs is questionable according to the focus of this paper.

[61] Recall that the countries of both clusters have very similar variable values, except for the fact that those of cluster 1 are landlocked and those of cluster 3 not.

In general, the analysis of this paper offers a new approach to group the countries of the world with new insight. Policy conclusions can be derived from specific analysis and description of each cluster. Deviations from the commonly used classification into LLDCs, LDCs and developed countries appeared rising criticism on it.

The *factor analysis* detected three main factors that account for 75% of the variance among the included variables. Hence, these three factors can be regarded as being the driving forces to divide the countries of the world into sub-groups. One is a well-being indicator being expressed by the variables *GDP* and *phone lines per capita*, the second factor describes demographic density of a region, being mainly driven by the variables *population density* and *roads per area*. The third factor appears to be a geographic one, being driven by the variable *landlocked*.

The fact that the variable *landlocked*, is the only binary variable and has a strong effect on the clustering outcome, motivated a separate analysis omitting this variable. The resulting clusters differed from those obtained by including the variable, however, the key results presented above are not altered. Hence, those clusters obtained from the *cluster analysis* with the variable *landlocked* are the core result from the analysis of this paper and serve as a new way of structuring the countries of the world.

However, it should always be kept in mind that the analysis of this paper has a specific focus omitting other variables that do also have an effect on economic and social development. Thus, the policy conclusions are valid and helpful, when keeping in mind this limitation.

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Appendix

A. List of Abbreviations

EU	European Union
GDP	Gross Domestic Product
GNI	Gross National Income
GNP	Gross National Product
HDI	Human Development Indicator
IMF	International Monetary Fund
LDCs	Less Developed Countries
LLDCs	Least Developed Countries
OECD	Organization for Economic Cooperation and Development
PPP	Purchasing Power Parity
R&D	Research & Development
SNA	System of National Accounting
TFP	Total Factor Productivity
UN	United Nations
UNICP	United Nations International Comparison Program
USSR/EE	Transition Economies of the former USSR and Eastern Europe
WTO	World Trade Organization

In the Tables:

GDP	GDP per capita measured in US$ purchasing power parity
PAV	percentage of the overall roads that are paved
URB	percentage of the population living in urban areas
RPA	kms of road per km^2 of area
PRIM	percentage of a population living in the largest city or metropolitan area
POPD	population density (population per area)
EPPC	electricity production per capita (in 1000 kwh per capita)
PHL	main phone lines in use per capita
LL	landlocked (0=landlocked, 1=access to sea)

B. Table I - The Raw Data[62]

Country	GDP	PAV	URB	RPA	PRIM	POPD	EPPC	PHL	LL
Afghanistan	800	13.3	22	0.032	9.3	42.865	0.014	0.001	0
Albania	3800	39	42	0.626	8.4	123.278	1.337	0.034	1
Algeria	5600	68.9	57	0.044	45.9	13.552	0.730	0.071	1
American Samoa*	8000	42.9	53	1.759	13.0	346.734	1.884	0.188	1
Andorra	19000	73.6	92	0.575	31.8	145.299	0	0.485	0
Angola	1330	10.4	34	0.061	24.3	8.497	0.011	0.007	1
Antigua and Barbuda	10000	33.0	37	2.630	44.8	151.242	1.493	0.418	1
Argentina	12000	29.4	88	0.078	33.3	13.666	2.190	0.198	1
Armenia	3350	96.3	67	0.379	37.5	111.745	1.709	0.171	0
Australia	24000	38.7	91	0.119	18.7	2.545	10.360	0.514	1
Austria	27000	100.0	67	1.590	25.3	97.415	7.380	0.490	0
Azerbaijan	3100	92.3	52	0.424	24.9	90.046	2.257	0.085	0
Bahamas	16800	57.4	89	0.193	57.1	21.593	5.116	0.319	1
Bahrain	13000	77.6	92	4.758	22.3	986.466	8.788	0.232	1
Bangladesh	1750	9.5	25	1.397	9.2	926.229	0.101	0.004	1
Barbados	14500	95.0	50	3.828	2.2	642.691	2.671	0.390	1
Belarus	8200	89.0	69	0.473	17.1	49.783	2.386	0.224	0
Belgium	26100	78.2	97	4.778	10.9	336.775	7.722	0.464	1
Belize	3250	17.0	48	0.125	2.7	11.452	0.730	0.118	1
Benin	1040	20.0	42	0.060	10.4	60.273	0.035	0.008	1
Bermuda	34800	100.0	100	8.491	1.7	1,207.547	9.297	0.813	1
Bhutan	1200	60.7	7	0.070	0.4	44.553	0.896	0.003	0
Bolivia	2600	6.5	62	0.045	17.5	7.687	0.458	0.039	0
Bosnia and Herzegovina	1800	52.3	43	0.427	9.1	77.529	0.660	0.076	1
Botswana	7800	55.0	49	0.017	13.4	2.650	0.314	0.094	0
Brazil	7400	5.5	81	0.233	10.1	20.680	1.945	0.097	1
Brunei Darussalam	18000	34.7	72	0.297	14.2	60.832	6.325	0.225	1
Bulgaria	6200	94.0	67	0.336	15.6	68.713	5.096	0.418	1

[62]The variables are defined in Appendix A. Countries marked with an asterisk (*) have missing or not perfectly compatible data. The data sources and the years of estimation are given in the text in Chapter 3.

Continuation of Table I

Country	GDP	PAV	URB	RPA	PRIM	POPD	EPPC	PHL	LL
Burkina Faso	1040	16.0	17	0.046	9.0	45.963	0.022	0.004	0
Burundi	600	7.1	9	0.520	3.7	228.997	0.023	0.003	0
Cambodia	1500	16.2	17	0.198	7.7	70.565	0.010	0.002	1
Cameroon	1700	12.5	49	0.072	10.3	34.040	0.224	0.006	1
Canada	27700	35.3	79	0.090	14.6	3.198	18.062	0.580	1
Cape Verde	1500	78.0	62	0.273	23.2	101.413	0.100	0.149	1
Central African Republic	1300	2.7	41	0.038	17.5	5.848	0.029	0.005	0
Chad	1030	0.8	24	0.026	11.6	7.007	0.010	0.001	0
Chile	10000	19.4	86	0.105	35.7	20.476	2.554	0.168	1
China a	4300	22.4	36	0.146	1.0	133.814	1.019	0.105	1
Colombia	6300	14.4	75	0.097	15.3	36.006	1.057	0.133	1
Comoros	710	76.5	33	0.406	4.9	282.949	0.031	0.011	1
Congo, Republic	900	9.7	65	0.037	20.2	8.649	0.102	0.007	1
Cook Islands*	5000		59	1.333	49.2	87.500	1.143	0.238	1
Costa Rica	8500	22.0	59	0.729	25.8	75.029	1.796	0.117	1
Cte d'Ivoire	1550	9.7	44	0.156	19.7	52.115	0.243	0.016	1
Croatia	8300	85.0	58	0.495	19.8	77.659	2.409	0.392	1
Cuba	2300	49.0	75	0.549	20.1	101.245	1.325	0.042	1
Cyprus*	13240	57.2	70	1.439	23.6	82.919	4.081	0.636	1
Czech Republic	14400	100.0	75	0.703	12.0	130.056	6.785	0.377	0
Dem. Republic of Congo	590	9.7	30	0.067	9.2	23.546	0.095	0.000	1
Denmark	28000	100.0	85	1.659	25.9	124.565	6.668	0.891	1
Djibouti	1400	12.6	84	0.126	48.7	28.304	0.276	0.015	1
Dominica	3700	50.0	71	1.034	23.2	92.838	0.957	0.271	1
Dominican Republic	5800	49.4	65	0.259	41.3	178.986	1.086	0.081	1
Ecuador	3000	18.9	63	0.152	13.0	47.422	0.773	0.009	1
Egypt	3700	78.1	43	0.064	15.0	70.610	0.984	0.056	1
El Salvador	4600	19.8	60	0.477	22.2	301.949	0.581	0.060	1

Continuation of Table I

Country	GDP	PAV	URB	RPA	PRIM	POPD	EPPC	PHL	LL
Equatorial Guinea	2100	0.0	48	0.103	6.1	17.753	0.044	0.008	1
Eritrea	740	21.8	19	0.032	8.0	36.812	0.047	0.007	1
Estonia	10000	20.1	69	0.670	28.5	31.309	4.983	0.354	1
Ethiopia	700	12.0	16	0.021	3.9	60.040	0.024	0.003	0
Fiji	5200	49.3	49	0.188	20.4	46.853	0.602	0.095	1
Finland	25800	64.5	59	0.231	22.5	15.378	14.539	0.552	1
France	25400	100.0	75	1.632	16.1	109.255	8.599	0.583	1
French Guyana	6000	45.0	75	0.020	22.6	2.000	2.473	0.258	1
French Polynesia	5000	33.3	53	0.190	9.2	61.675	1.588	0.202	1
Gabon	5500	9.9	81	0.029	42.7	4.606	0.689	0.032	1
Gambia	1770	35.4	31	2.389	13.7	1,288.496	0.052	0.022	1
Georgia	3100	93.5	56	0.486	25.6	71.176	1.492	0.125	1
Germany	26200	99.1	88	1.838	4.0	233.185	6.454	0.611	1
Ghana	1980	29.6	36	0.163	9.8	84.540	0.292	0.012	1
Greece	17900	91.8	60	0.887	29.3	80.681	4.658	0.510	1
Grenada	4750	61.3	38	3.023	5.4	258.721	1.236	0.303	1
Guadeloupe	9000	37.7	100	1.438	6.8	244.944	3.188	0.392	1
Guam*	21000		39	1.612	0.7	293.260	5.124	0.523	1
Guatemala	3700	34.5	40	0.127	24.4	122.270	0.445	0.050	1
Guinea	1970	16.5	27	0.124	23.5	31.624	0.099	0.005	1
Guinea-Bissau	900	10.3	32	0.122	20.8	37.237	0.045	0.007	1
Guyana	3600	7.4	36	0.037	10.3	3.247	0.723	0.100	1
Haiti	1700	24.3	36	0.150	12.0	254.523	0.074	0.008	1
Honduras	2600	20.4	53	0.137	14.5	58.533	0.545	0.036	1
Hungary	12000	43.4	65	2.023	18.1	108.298	3.319	0.307	0
Iceland	24800	29.5	92	0.123	61.2	2.709	27.057	0.602	1
India	2500	45.7	28	1.010	1.7	318.119	0.523	0.026	1
Indonesia	3000	46.3	41	0.179	4.8	120.518	0.400	0.024	1
Iran (Islamic Rep. of)	6400	56.3	64	0.085	10.8	40.427	1.806	0.095	1
Iraq	2500	84.3	68	0.104	20.0	54.915	1.137	0.028	1
Ireland	27300	94.1	59	1.316	25.4	55.250	5.739	0.409	1

Continuation of Table I

Country	GDP	PAV	URB	RPA	PRIM	POPD	EPPC	PHL	LL
Israel	20000	100.0	92	0.769	36.2	290.323	6.447	0.464	1
Italy	24300	100.0	67	2.220	7.4	191.601	4.460	0.433	1
Jamaica	3700	70.1	56	1.729	34.0	243.836	2.515	0.132	1
Japan	27200	46.0	79	3.049	20.8	336.059	7.994	0.476	1
Jordan	4200	100.0	79	0.087	26.9	57.497	1.306	0.076	1
Kazakhstan	5900	94.7	56	0.070	7.5	6.161	2.908	0.115	0
Kenya	1000	12.1	33	0.109	7.4	53.444	0.148	0.010	1
Kiribati*	840		38	0.826	18.7	118.372	0.073	0.040	1
Korea, Dem. People's Rep. of	1000	6.4	60	0.259	12.3	184.370	1.503	0.049	1
Korea, Republic of	18000	74.5	82	0.889	20.5	490.699	5.654	0.497	1
Kuwait	15100	80.6	96	0.250	56.3	118.519	14.773	0.195	1
Kyrgyzstan	2800	91.1	34	0.153	16.4	24.292	3.044	0.073	0
Lao People's Dem. Rep.	1630	13.8	19	0.059	10.9	24.396	0.177	0.004	0
Latvia	7800	38.6	60	0.916	32.7	36.647	1.395	0.314	1
Lebanon	5200	84.9	90	0.702	55.9	353.654	2.162	0.190	1
Lesotho	2450	18.3	28	0.163	5.2	72.739	0.000	0.010	0
Liberia	1100	6.2	45	0.095	41.0	29.523	0.137	0.002	1
Libyan Arab Jamahiriya	7600	57.2	88	0.014	19.6	3.051	3.613	0.071	1
Liechtenstein	23000	100.0	21	1.563	15.1	206.250	0.000	0.606	0
Lithuania	7600	91.3	69	0.675	16.1	55.230	3.045	0.317	1
Luxembourg	43400	100.0	92	1.998	17.4	173.627	1.042	0.701	0
Madagascar	870	11.6	29	0.051	9.1	28.061	0.050	0.003	1
Malawi	660	18.5	15	0.123	4.8	90.327	0.077	0.004	0
Malaysia	9000	75.8	57	0.196	6.1	68.725	2.783	0.203	1
Maledives*	3870		28		9.2	1,066.667	0.344	0.066	1
Mali	840	12.1	30	0.012	10.0	9.145	0.041	0.004	0
Malta	15000	87.5	91	5.513	1.8	1,256.329	4.408	0.471	1
Marshall Islands*	1600		66		27.0	408.840	0.000	0.057	1

Continuation of Table I

Country	**GDP**	**PAV**	**URB**	**RPA**	**PRIM**	**POPD**	**EPPC**	**PHL**	**LL**
Martinique*	11000		95	1.914	31.7	383.636	2.666	0.403	1
Mauritania	1800	11.3	58	0.007	17.0	2.745	0.054	0.009	1
Mauritius	10800	97.0	41	0.912	12.1	588.235	1.071	0.204	1
Mexico	9000	32.8	74	0.164	17.5	52.419	1.880	0.119	1
Micronesia, Fed. States of	2000	17.5	28	0.342	4.6	193.732	0.000	0.081	1
Monaco	27000	100.0	100	25.000	100.0	16,000.000	0.000	0.970	1
Mongolia	1770	3.5	57	0.002	27.4	1.721	1.028	0.039	0
Morocco	3700	56.4	55	0.130	11.4	69.797	0.457	0.045	1
Mozambique	900	18.7	32	0.038	15.4	24.461	0.358	0.005	1
Myanmar	1500	12.2	28	0.042	9.9	62.252	0.113	0.006	1
Namibia	4500	13.6	31	0.079	10.5	2.216	0.016	0.060	1
Nauru	5000	80.0	100	1.429	33.3	571.429	2.500	0.167	1
Nepal	1400	30.8	12	0.094	2.1	183.764	0.056	0.009	0
Netherlands	25800	90.0	89	2.805	7.1	386.938	5.474	0.568	1
Netherlands Antilles	11400	50.0	69	0.625	67.8	222.917	5.491	0.355	1
New Caledonia	15000	47.4	77	0.253	46.9	10.913	7.524	0.226	1
New Zealand	19500	62.8	86	0.343	28.2	14.545	9.167	0.491	1
Nicaragua	2500	11.0	56	0.127	19.1	38.797	0.444	0.028	1
Niger	820	7.9	21	0.008	4.7	8.398	0.021	0.002	0
Nigeria	840	30.9	44	0.209	10.3	140.658	0.122	0.004	1
Northern Mariana Islands*	12500		53	0.759	61.0	161.426	0.000	0.273	1
Norway	30800	76.0	75	0.266	21.6	13.222	31.196	0.604	1
Oman	8200	30.0	76	0.154	3.1	12.769	2.986	0.074	1
Pakistan	2100	43.0	33	0.308	8.0	183.674	0.425	0.019	1
Palau	9000	59.0	69	0.133	55.3	41.485	0.000	0.353	1
Panama	5900	34.6	56	0.148	40.7	36.854	1.698	0.137	1
Papua New Guinea	2400	3.5	17	0.042	5.8	11.174	0.319	0.012	1
Paraguay	4600	9.5	56	0.064	21.4	14.466	9.017	0.049	0
Peru	4800	12.8	73	0.057	26.6	21.747	0.704	0.054	1
Philippines	4000	21.0	59	0.667	12.9	281.753	0.481	0.037	1

Continuation of Table I

Country	GDP	PAV	URB	RPA	PRIM	POPD	EPPC	PHL	LL
Poland	8800	68.3	62	1.219	9.0	123.527	3.499	0.209	1
Portugal	17300	86.0	64	0.744	37.9	109.145	4.288	0.526	1
Puerto Rico	11200	100.0	75	1.582	34.8	435.852	5.166	0.333	1
Qatar	21200	90.0	93	0.108	39.5	69.336	11.602	0.179	1
Republic of Moldova	2550	87.0	42	0.591	14.8	131.046	0.748	0.141	0
Reunion	4800	47.7	71	1.084	13.4	296.178	1.465	0.361	1
Romania	6800	49.5	55	0.646	9.2	93.971	2.231	0.169	1
Russian Federation	8300	67.4	73	0.056	6.4	8.491	5.763	0.207	1
Rwanda	1000	8.3	6	0.456	4.7	280.887	0.015	0.001	0
Saint Kitts and Nevis	8700	42.5	34	1.226	36.3	149.425	2.436	0.436	1
Saint Lucia	4400	5.2	38	1.964	34.1	259.740	0.719	0.231	1
Saint Vincent / Grenadines	2900	30.8	55	2.674	13.9	298.201	0.707	0.177	1
Samoa	3500	31.9	22	0.284	19.1	60.802	0.575	0.046	1
San Marino	34600	100.0	90	3.607	16.1	459.016	0.000	0.643	0
Sao Tome and Principe	1200	68.1	47	0.320	25.5	169.830	0.100	0.018	1
Saudi Arabia	10600	30.1	86	0.075	15.0	11.993	5.252	0.132	1
Senegal	1580	29.3	47	0.074	19.6	53.978	0.125	0.022	1
Seychelles	7600	84.5	64	0.615	37.5	175.824	2.000	0.245	1
Sierra Leone	500	7.9	37	0.163	18.0	78.269	0.044	0.004	1
Singapore	24700	100.0	100	4.545	80.1	6,425.685	6.265	0.438	1
Slovakia	11500	86.7	57	0.363	8.3	111.004	5.077	0.357	0
Slovenia	16000	99.9	49	0.966	15.0	95.398	6.627	0.373	1
Solomon Islands	1700	2.5	20	0.048	6.1	17.399	0.065	0.016	1
Somalia	550	11.8	27	0.035	15.7	12.159	0.032	0.000	1
South Africa	9400	20.3	57	0.294	6.9	35.780	4.453	0.115	1
Spain	18900	99.0	78	0.687	10.2	79.395	5.281	0.433	1
Sri Lanka	3250	95.0	23	0.172	4.0	298.384	0.338	0.025	1
Sudan	1360	36.3	36	0.005	7.4	14.802	0.053	0.011	1
Suriname	3500	26.0	74	0.028	49.0	2.670	3.227	0.147	1
Swaziland	4200	28.2	26	0.219	4.6	64.735	0.322	0.034	0

Continuation of Table I

Country	**GDP**	**PAV**	**URB**	**RPA**	**PRIM**	**POPD**	**EPPC**	**PHL**	**LL**
Sweden	24700	78.4	83	0.468	17.8	19.728	16.292	0.678	1
Switzerland	31100	100.0	67	1.721	12.8	176.847	8.790	0.660	0
Syrian Arab Republic	3200	23.1	51	0.224	10.8	92.645	1.148	0.077	1
Tajikistan	1140	82.7	28	0.209	9.2	46.960	2.120	0.054	0
Thailand	6600	97.5	20	0.126	11.7	121.311	1.513	0.090	1
The FYR of Macedonia	4400	63.8	59	0.343	25.3	81.119	3.112	0.199	0
Togo	1500	31.6	33	0.132	9.7	93.088	0.018	0.005	1
Tonga	2200	27.0	33	0.909	32.1	141.711	0.283	0.075	1
Trinidad and Tobago	9000	51.1	74	1.622	4.4	226.989	4.427	0.216	1
Tunisia	6600	64.8	66	0.141	19.3	59.996	1.049	0.067	1
Turkey	6700	34.0	66	0.489	14.0	86.223	1.771	0.290	1
Turkmenistan	4700	81.8	45	0.045	11.0	9.607	1.974	0.077	0
Tuvalu	1100	0.0	52	0.750	36.4	423.077	0.000	0.091	1
Uganda	1200	6.7	14	0.114	4.9	104.639	0.065	0.002	0
Ukraine	4200	96.7	68	0.453	5.5	80.166	3.380	0.195	1
United Arab Emirates	21100	100.0	87	0.058	37.9	29.513	15.822	0.374	1
United Kingdom	24700	100.0	89	1.518	12.8	244.171	5.951	0.583	1
United Rep. of Tanzania	610	4.2	32	0.090	6.3	39.349	0.074	0.003	1
United States of America	36300	58.8	77	0.662	5.9	29.137	13.544	0.691	1
U.S. Virgin Islands*	15000		46	2.432	10.1	352.273	8.226	0.500	1
Uruguay	9200	90.0	92	0.050	36.5	19.220	2.222	0.274	1
Uzbekistan	2500	87.3	37	0.182	8.4	57.137	1.724	0.077	0
Vanuatu	1300	23.9	22	0.088	17.2	16.066	0.199	0.028	1
Venezuela	6100	33.6	87	0.105	13.0	26.630	3.325	0.107	1
Vietnam	2100	25.1	24	0.283	3.7	246.080	0.318	0.032	1
Yemen	820	11.5	25	0.131	8.8	35.421	0.171	0.016	1
Yugoslavia	2250	62.3	52	0.475	13.9	104.123	3.095	0.189	1
Zambia	870	18.0	40	0.089	16.5	13.233	0.785	0.013	0
Zimbabwe	2450	47.4	35	0.047	15.4	29.128	0.565	0.019	0

C. Table II - Ward Clustering with Raw Data[63]

Country	8 Clusters	15 Clusters	GDP	Country	8 Clusters	15 Clusters	GDP
Sierra Leone	1	1	500	Liberia	1	1	1100
Somalia	1	1	550	Tuvalu	1	1	1100
Dem. Republic of Congo	1	1	590	Tajikistan	1	2	1140
Burundi	1	1	600	Bhutan	1	2	1200
United Rep. of Tanzania	1	1	610	Sao Tome and Principe	1	2	1200
Malawi	1	1	660	Uganda	1	2	1200
Ethiopia	1	1	700	Central African Republic	1	2	1300
Comoros	1	1	710	Vanuatu	1	2	1300
Eritrea	1	1	740	Angola	1	2	1330
Afghanistan	1	1	800	Sudan	1	2	1360
Niger	1	1	820	Djibouti	1	2	1400
Yemen	1	1	820	Nepal	1	2	1400
Mali	1	1	840	Cambodia	1	2	1500
Nigeria	1	1	840	Cape Verde	1	2	1500
Madagascar	1	1	870	Myanmar	1	2	1500
Zambia	1	1	870	Togo	1	2	1500
Congo, Republic	1	1	900	Cte d'Ivoire	1	2	1550
Guinea-Bissau	1	1	900	Senegal	1	2	1580
Mozambique	1	1	900	Lao People's Dem. Rep.	1	2	1630
Kenya	1	1	1000	Cameroon	1	2	1700
Korea, Dem. People's Rep. of	1	1	1000	Haiti	1	2	1700
Rwanda	1	1	1000	Solomon Islands	1	2	1700

[63]The countries marked with an asterisk (*) in Table 1 are left out.

Continuation of Table II

Country	**8 Clusters**	**15 Clusters**	**GDP**	**Country**	**8 Clusters**	**15 Clusters**	**GDP**
Chad	1	1	1030	Bangladesh	1	2	1750
Benin	1	1	1040	Gambia	1	2	1770
Burkina Faso	1	1	1040	Mongolia	1	2	1770
Bosnia and Herzegovina	1	2	1800	China	2	3	4300
Mauritania	1	2	1800	Guinea	2	4	1970
Kyrgyzstan	2	3	2800	Ghana	2	4	1980
Saint Vincent / Grenadines	2	3	2900	Micronesia, Fed. States of	2	4	2000
Ecuador	2	3	3000	Equatorial Guinea	2	4	2100
Indonesia	2	3	3000	Pakistan	2	4	2100
Azerbaijan	2	3	3100	Vietnam	2	4	2100
Georgia	2	3	3100	Tonga	2	4	2200
Syrian Arab Republic	2	3	3200	Yugoslavia	2	4	2250
Belize	2	3	3250	Cuba	2	4	2300
Sri Lanka	2	3	3250	Papua New Guinea	2	4	2400
Armenia	2	3	3350	Lesotho	2	4	2450
Samoa	2	3	3500	Zimbabwe	2	4	2450
Suriname	2	3	3500	India	2	4	2500
Guyana	2	3	3600	Iraq	2	4	2500
Dominica	2	3	3700	Nicaragua	2	4	2500
Egypt	2	3	3700	Uzbekistan	2	4	2500
Guatemala	2	3	3700	Republic of Moldova	2	4	2550
Jamaica	2	3	3700	Bolivia	2	4	2600
Morocco	2	3	3700	Honduras	2	4	2600
Albania	2	3	3800	Gabon	3	5	5500
Philippines	2	3	4000	Algeria	3	5	5600
Jordan	2	3	4200	Dominican Republic	3	5	5800
Swaziland	2	3	4200	Kazakhstan	3	5	5900
Ukraine	2	3	4200	Panama	3	5	5900

Continuation of Table II

Country	**8 Clusters**	**15 Clusters**	**GDP**	**Country**	**8 Clusters**	**15 Clusters**	**GDP**
French Guyana	3	5	6000	Seychelles	4	7	7600
Venezuela	3	5	6100	Botswana	4	7	7800
Bulgaria	3	5	6200	Latvia	4	7	7800
Colombia	3	5	6300	Belarus	4	7	8200
Iran (Islamic Rep. of)	3	5	6400	Oman	4	7	8200
Thailand	3	5	6600	Croatia	4	7	8300
Tunisia	3	5	6600	Russian Federation	4	7	8300
Turkey	3	5	6700	Costa Rica	4	7	8500
Romania	3	5	6800	Saint Kitts and Nevis	4	7	8700
Saint Lucia	3	6	4400	Poland	4	7	8800
The FYR of Macedonia	3	6	4400	Guadeloupe	4	7	9000
Namibia	3	6	4500	Malaysia	4	7	9000
El Salvador	3	6	4600	Mexico	4	7	9000
Paraguay	3	6	4600	Palau	4	7	9000
Turkmenistan	3	6	4700	Trinidad and Tobago	4	7	9000
Grenada	3	6	4750	Uruguay	4	7	9200
Peru	3	6	4800	South Africa	4	7	9400
Reunion	3	6	4800	Antigua and Barbuda	4	7	10000
French Polynesia	3	6	5000	Chile	4	7	10000
Nauru	3	6	5000	Estonia	4	7	10000
Fiji	3	6	5200	Saudi Arabia	5	8	10600
Lebanon	3	6	5200	Mauritius	5	8	10800
Brazil	4	7	7400	Puerto Rico	5	8	11200
Libyan Arab Jamahiriya	4	7	7600	Netherlands Antilles	5	8	11400
Lithuania	4	7	7600	Slovakia	5	8	11500

Continuation of Table II

Country	**8 Clusters**	**15 Clusters**	**GDP**	**Country**	**8 Clusters**	**15 Clusters**	**GDP**
Argentina	5	8	12000	United Kingdom	7	12	24700
Hungary	5	8	12000	Iceland	7	12	24800
Bahrain	5	8	13000	France	7	13	25400
Czech Republic	5	9	14400	Finland	7	13	25800
Barbados	5	9	14500	Netherlands	7	13	25800
Malta	5	9	15000	Belgium	7	13	26100
New Caledonia	5	9	15000	Germany	7	13	26200
Kuwait	5	9	15100	Austria	7	13	27000
Spain	6	10	18900	Monaco	7	13	27000
Andorra	6	10	19000	Japan	7	13	27200
New Zealand	6	10	19500	Ireland	7	13	27300
Israel	6	10	20000	Canada	7	13	27700
United Arab Emirates	6	10	21100	Denmark	7	13	28000
Qatar	6	10	21200	Norway	8	14	30800
Slovenia	6	11	16000	Switzerland	8	14	31100
Bahamas	6	11	16800	San Marino	8	14	34600
Portugal	6	11	17300	Bermuda	8	14	34800
Greece	6	11	17900	United States of America	8	14	36300
Brunei Darussalam	6	11	18000	Luxembourg	8	15	43400
Korea, Republic of	6	11	18000				
Liechtenstein	7	12	23000				
Australia	7	12	24000				
Italy	7	12	24300				
Singapore	7	12	24700				
Sweden	7	12	24700				

D. Table III - The Standardized Data used for the Analysis[64]

Country	GDP	PAV	URB	RPA	PRIM	POPD	EPPC	PHL	LL
Afghanistan	-0.826	-1.051	-1.393	-0.363	-0.626	-0.161	-0.640	-0.889	-1.927
Albania	-0.493	-0.280	-0.559	-0.076	-0.685	-0.096	-0.337	-0.733	0.516
Algeria	-0.294	0.617	0.067	-0.358	-0.941	-0.185	-0.476	-0.556	0.516
Andorra	1.192	0.758	1.527	-0.101	0.866	-0.078	-0.643	1.400	-1.927
Angola	-0.767	-1.138	-0.893	-0.349	0.368	-0.189	-0.640	-0.863	0.516
Antigua and Barbuda	0.194	-0.461	-0.768	0.893	1.732	-0.073	-0.301	1.085	0.516
Argentina	0.416	-0.568	1.360	-0.341	0.970	-0.185	-0.141	0.045	0.516
Armenia	-0.543	1.439	0.484	-0.195	1.250	-0.105	-0.251	-0.086	-1.927
Australia	1.746	-0.289	1.485	-0.321	-0.001	-0.194	1.729	1.538	0.516
Austria	2.078	1.550	0.484	0.390	0.439	-0.117	1.047	1.424	-1.927
Azerbaijan	-0.571	1.319	-0.142	-0.174	0.407	-0.123	-0.126	-0.491	-1.927
Bahamas	0.948	0.272	1.402	-0.285	2.554	-0.178	0.529	0.616	0.516
Bahrain	0.526	0.878	1.527	1.922	0.235	0.601	1.369	0.203	0.516
Bangladesh	-0.721	-1.165	-1.268	0.297	-0.633	0.553	-0.619	-0.876	0.516
Barbados	0.693	1.400	-0.225	1.473	-1.100	0.324	-0.031	0.952	0.516
Belarus	-0.006	1.220	0.568	-0.150	-0.106	-0.155	-0.096	0.166	-1.927
Belgium	1.979	0.896	1.736	1.932	-0.520	0.076	1.125	1.303	0.516
Belize	-0.554	-0.940	-0.309	-0.318	-1.067	-0.186	-0.476	-0.336	0.516
Benin	-0.799	-0.850	-0.559	-0.350	-0.557	-0.147	-0.635	-0.858	0.516
Bermuda	2.943	1.550	1.861	3.727	-1.132	0.780	1.486	2.952	0.516
Bhutan	-0.781	0.371	-2.019	-0.345	-1.218	-0.160	-0.438	-0.880	-1.927
Bolivia	-0.626	-1.255	0.275	-0.357	-0.081	-0.189	-0.538	-0.710	-1.927
Bosnia and Herzegovina	-0.715	0.119	-0.517	-0.172	-0.642	-0.133	-0.492	-0.532	0.516
Botswana	-0.050	0.200	-0.267	-0.371	-0.354	-0.194	-0.571	-0.447	-1.927
Brazil	-0.094	-1.285	1.068	-0.266	-0.574	-0.179	-0.197	-0.436	0.516
Brunei Darussalam	1.081	-0.409	0.693	-0.235	-0.299	-0.147	0.805	0.172	0.516
Bulgaria	-0.227	1.370	0.484	-0.216	-0.206	-0.140	0.524	1.086	0.516
Burkina Faso	-0.799	-0.970	-1.602	-0.357	-0.650	-0.159	-0.638	-0.874	-1.927
Burundi	-0.848	-1.237	-1.936	-0.127	-1.001	-0.011	-0.637	-0.879	-1.927

[64]For the 194 Countries (thos from Table I without the asterisk). Discussion of this table is given in Chapter 5.

Continuation of Table III

Country	GDP	PAV	URB	RPA	PRIM	POPD	EPPC	PHL	LL
Cambodia	-0.748	-0.964	-1.602	-0.283	-0.734	-0.139	-0.640	-0.886	0.516
Cameroon	-0.726	-1.075	-0.267	-0.344	-0.560	-0.168	-0.591	-0.866	0.516
Canada	2.156	-0.391	0.985	-0.335	-0.277	-0.193	3.492	1.851	0.516
Cape Verde	-0.748	0.890	0.275	-0.247	0.299	-0.114	-0.620	-0.188	0.516
Central African Republic	-0.770	-1.368	-0.601	-0.360	-0.085	-0.191	-0.636	-0.869	-1.927
Chad	-0.800	-1.425	-1.310	-0.366	-0.475	-0.190	-0.640	-0.888	-1.927
Chile	0.194	-0.868	1.277	-0.328	1.130	-0.179	-0.058	-0.099	0.516
China	-0.438	-0.778	-0.809	-0.308	-1.180	-0.088	-0.409	-0.396	0.516
Colombia	-0.216	-1.018	0.818	-0.332	-0.226	-0.167	-0.401	-0.267	0.516
Comoros	-0.836	0.845	-0.934	-0.183	-0.921	0.033	-0.636	-0.840	0.516
Congo, Republic	-0.815	-1.158	0.401	-0.361	0.094	-0.189	-0.619	-0.859	0.516
Costa Rica	0.028	-0.790	0.150	-0.026	0.468	-0.135	-0.231	-0.338	0.516
Cte d'Ivoire	-0.743	-1.159	-0.476	-0.303	0.062	-0.154	-0.587	-0.819	0.516
Croatia	0.006	1.101	0.109	-0.139	0.068	-0.133	-0.091	0.962	0.516
Cuba	-0.660	0.020	0.818	-0.113	0.091	-0.114	-0.339	-0.694	0.516
Czech Republic	0.682	1.550	0.818	-0.039	-0.451	-0.091	0.910	0.892	-1.927
Dem. Republic of Congo	-0.849	-1.159	-1.060	-0.346	-0.636	-0.177	-0.621	-0.892	0.516
Denmark	2.189	1.550	1.235	0.423	0.473	-0.095	0.884	3.326	0.516
Djibouti	-0.759	-1.072	1.193	-0.318	1.993	-0.173	-0.579	-0.821	0.516
Dominica	-0.504	0.050	0.651	0.121	0.297	-0.121	-0.424	0.391	0.516
Dominican Republic	-0.272	0.032	0.401	-0.254	1.498	-0.051	-0.394	-0.509	0.516
Ecuador	-0.582	-0.883	0.317	-0.305	-0.379	-0.157	-0.466	-0.853	0.516
Egypt	-0.504	0.893	-0.517	-0.348	-0.249	-0.139	-0.417	-0.628	0.516
El Salvador	-0.405	-0.856	0.192	-0.148	0.228	0.048	-0.510	-0.611	0.516
Equatorial Guinea	-0.682	-1.449	-0.309	-0.329	-0.840	-0.181	-0.633	-0.856	0.516
Eritrea	-0.832	-0.796	-1.519	-0.363	-0.713	-0.166	-0.632	-0.862	0.516
Estonia	0.194	-0.847	0.568	-0.055	0.651	-0.170	0.498	0.783	0.516
Ethiopia	-0.837	-1.090	-1.644	-0.368	-0.987	-0.147	-0.637	-0.878	-1.927
Fiji	-0.338	0.029	-0.267	-0.288	0.111	-0.158	-0.505	-0.446	0.516
Finland	1.945	0.485	0.150	-0.267	0.251	-0.183	2.686	1.719	0.516

Continuation of Table III

Country	GDP	PAV	URB	RPA	PRIM	POPD	EPPC	PHL	LL
France	1.901	1.550	0.818	0.411	-0.175	-0.107	1.326	1.867	0.516
French Guyana	-0.249	-0.101	0.818	-0.369	0.258	-0.194	-0.077	0.329	0.516
French Polynesia	-0.360	-0.450	-0.100	-0.287	-0.637	-0.146	-0.279	0.064	0.516
Gabon	-0.305	-1.153	1.068	-0.365	1.592	-0.192	-0.485	-0.744	0.516
Gambia	-0.718	-0.388	-1.018	0.777	-0.333	-0.092	-0.631	-0.790	0.516
Georgia	-0.571	1.355	0.025	-0.144	0.454	-0.138	-0.301	-0.302	0.516
Germany	1.990	1.523	1.360	0.510	-0.981	-0.007	0.835	2.001	0.516
Ghana	-0.695	-0.562	-0.809	-0.300	-0.597	-0.127	-0.576	-0.838	0.516
Greece	1.070	1.304	0.192	0.050	0.701	-0.130	0.424	1.521	0.516
Grenada	-0.388	0.390	-0.726	1.083	-0.889	0.013	-0.360	0.542	0.516
Guadeloupe	0.083	-0.319	1.861	0.317	-0.796	0.002	0.087	0.963	0.516
Guatemala	-0.504	-0.415	-0.642	-0.317	0.373	-0.097	-0.541	-0.657	0.516
Guinea	-0.696	-0.955	-1.185	-0.319	0.314	-0.170	-0.620	-0.871	0.516
Guinea-Bissau	-0.815	-1.141	-0.976	-0.320	0.138	-0.166	-0.632	-0.859	0.516
Guyana	-0.515	-1.227	-0.809	-0.361	-0.560	-0.193	-0.477	-0.419	0.516
Haiti	-0.726	-0.721	-0.809	-0.306	-0.449	0.010	-0.626	-0.854	0.516
Honduras	-0.626	-0.838	-0.100	-0.312	-0.283	-0.148	-0.518	-0.725	0.516
Hungary	0.416	-0.148	0.401	0.599	-0.042	-0.108	0.117	0.560	-1.927
Iceland	1.834	-0.565	1.527	-0.319	2.825	-0.193	5.551	1.957	0.516
India	-0.637	-0.079	-1.143	0.109	-1.131	0.061	-0.523	-0.768	0.516
Indonesia	-0.582	-0.061	-0.601	-0.292	-0.930	-0.098	-0.551	-0.779	0.516
Iran (Islamic Rep. of)	-0.205	0.239	0.359	-0.338	-0.525	-0.163	-0.229	-0.445	0.516
Iraq	-0.637	1.079	0.526	-0.328	0.083	-0.151	-0.382	-0.761	0.516
Ireland	2.112	1.373	0.150	0.258	0.441	-0.151	0.671	1.045	0.516
Israel	1.302	1.550	1.527	-0.007	1.159	0.039	0.833	1.304	0.516
Italy	1.779	1.550	0.484	0.695	-0.756	-0.041	0.378	1.157	0.516
Jamaica	-0.504	0.653	0.025	0.457	1.018	0.001	-0.067	-0.270	0.516
Japan	2.100	-0.070	0.985	1.096	0.137	0.076	1.187	1.357	0.516
Jordan	-0.449	1.550	0.985	-0.337	0.546	-0.149	-0.344	-0.534	0.516
Kazakhstan	-0.261	1.391	0.025	-0.345	-0.751	-0.191	0.023	-0.351	-1.927

Continuation of Table III

Country	GDP	PAV	URB	RPA	PRIM	POPD	EPPC	PHL	LL
Kenya	-0.804	-1.087	-0.934	-0.326	-0.753	-0.152	-0.609	-0.847	0.516
Korea, Dem. People's Rep. of	-0.804	-1.258	0.192	-0.254	-0.426	-0.047	-0.299	-0.659	0.516
Korea, Republic of	1.081	0.785	1.110	0.051	0.115	0.201	0.652	1.457	0.516
Kuwait	0.759	0.968	1.694	-0.258	2.501	-0.100	2.739	0.030	0.516
Kyrgyzstan	-0.604	1.283	-0.893	-0.305	-0.152	-0.176	0.054	-0.549	-1.927
Lao People's Dem. Rep.	-0.734	-1.036	-1.519	-0.350	-0.518	-0.176	-0.602	-0.873	-1.927
Latvia	-0.050	-0.292	0.192	0.064	0.931	-0.166	-0.323	0.594	0.516
Lebanon	-0.338	1.097	1.444	-0.039	2.470	0.090	-0.148	0.007	0.516
Lesotho	-0.643	-0.901	-1.143	-0.300	-0.901	-0.137	-0.643	-0.846	-1.927
Liberia	-0.793	-1.264	-0.434	-0.333	1.480	-0.172	-0.611	-0.884	0.516
Libyan Arab Jamahiriya	-0.072	0.266	1.360	-0.372	0.054	-0.193	0.185	-0.559	0.516
Liechtenstein	1.635	1.550	-1.435	0.377	-0.244	-0.029	-0.643	1.975	-1.927
Lithuania	-0.072	1.289	0.568	-0.052	-0.178	-0.151	0.054	0.607	0.516
Luxembourg	3.896	1.550	1.527	0.587	-0.086	-0.055	-0.404	2.424	-1.927
Madagascar	-0.818	-1.102	-1.101	-0.354	-0.638	-0.173	-0.631	-0.878	0.516
Malawi	-0.841	-0.895	-1.685	-0.319	-0.924	-0.123	-0.625	-0.877	-1.927
Malaysia	0.083	0.824	0.067	-0.284	-0.842	-0.140	-0.006	0.067	0.516
Mali	-0.821	-1.087	-1.060	-0.373	-0.583	-0.188	-0.633	-0.875	-1.927
Malta	0.748	1.175	1.485	2.287	-1.127	0.819	0.366	1.336	0.516
Mauritania	-0.715	-1.111	0.109	-0.375	-0.117	-0.193	-0.630	-0.849	0.516
Mauritius	0.283	1.460	-0.601	0.062	-0.440	0.280	-0.398	0.073	0.516
Mexico	0.083	-0.466	0.776	-0.299	-0.082	-0.153	-0.212	-0.329	0.516
Micronesia, Fed. States of	-0.693	-0.925	-1.143	-0.213	-0.943	-0.039	-0.643	-0.511	0.516
Monaco	2.078	1.550	1.861	11.711	5.405	12.732	-0.643	3.696	0.516
Mongolia	-0.718	-1.345	0.067	-0.378	0.576	-0.194	-0.407	-0.711	-1.927
Morocco	-0.504	0.242	-0.017	-0.316	-0.491	-0.139	-0.538	-0.682	0.516
Mozambique	-0.815	-0.889	-0.976	-0.360	-0.220	-0.176	-0.561	-0.872	0.516
Myanmar	-0.748	-1.084	-1.143	-0.359	-0.586	-0.145	-0.617	-0.866	0.516
Namibia	-0.416	-1.042	-1.018	-0.341	-0.547	-0.194	-0.639	-0.609	0.516
Nauru	-0.360	0.950	1.861	0.312	0.971	0.266	-0.070	-0.105	0.516

Continuation of Table III

Country	GDP	PAV	URB	RPA	PRIM	POPD	EPPC	PHL	LL
Nepal	-0.759	-0.526	-1.811	-0.333	-1.109	-0.047	-0.630	-0.850	-1.927
Netherlands	1.945	1.250	1.402	0.978	-0.773	0.117	0.610	1.797	0.516
Netherlands Antilles	0.349	0.050	0.568	-0.077	3.260	-0.016	0.614	0.787	0.516
New Caledonia	0.748	-0.028	0.901	-0.256	1.874	-0.187	1.080	0.176	0.516
New Zealand	1.247	0.434	1.277	-0.213	0.629	-0.184	1.456	1.432	0.516
Nicaragua	-0.637	-1.120	0.025	-0.318	0.023	-0.164	-0.541	-0.762	0.516
Niger	-0.824	-1.213	-1.435	-0.375	-0.932	-0.189	-0.638	-0.885	-1.927
Nigeria	-0.821	-0.523	-0.476	-0.278	-0.560	-0.082	-0.615	-0.876	0.516
Norway	2.500	0.830	0.818	-0.250	0.191	-0.185	6.499	1.967	0.516
Oman	-0.006	-0.550	0.860	-0.304	-1.038	-0.185	0.041	-0.543	0.516
Pakistan	-0.682	-0.160	-0.934	-0.230	-0.715	-0.047	-0.545	-0.802	0.516
Palau	0.083	0.320	0.568	-0.314	2.429	-0.162	-0.643	0.776	0.516
Panama	-0.261	-0.412	0.025	-0.307	1.461	-0.166	-0.254	-0.243	0.516
Papua New Guinea	-0.648	-1.345	-1.602	-0.358	-0.860	-0.187	-0.570	-0.838	0.516
Paraguay	-0.405	-1.165	0.025	-0.348	0.180	-0.184	1.422	-0.660	-1.927
Peru	-0.382	-1.066	0.734	-0.351	0.525	-0.178	-0.481	-0.638	0.516
Philippines	-0.471	-0.820	0.150	-0.057	-0.389	0.032	-0.533	-0.720	0.516
Poland	0.061	0.599	0.275	0.210	-0.646	-0.096	0.158	0.095	0.516
Portugal	1.003	1.130	0.359	-0.019	1.277	-0.107	0.339	1.594	0.516
Puerto Rico	0.327	1.550	0.818	0.386	1.069	0.157	0.540	0.683	0.516
Qatar	1.435	1.250	1.569	-0.327	1.384	-0.140	2.013	-0.046	0.516
Republic of Moldova	-0.632	1.160	-0.559	-0.093	-0.261	-0.090	-0.471	-0.225	-1.927
Reunion	-0.382	-0.018	0.651	0.146	-0.352	0.044	-0.307	0.815	0.516
Romania	-0.161	0.035	-0.017	-0.067	-0.634	-0.120	-0.132	-0.093	0.516
Russian Federation	0.006	0.572	0.734	-0.352	-0.819	-0.189	0.677	0.086	0.516
Rwanda	-0.804	-1.201	-2.061	-0.158	-0.930	0.031	-0.639	-0.887	-1.927
Saint Kitts and Nevis	0.050	-0.175	-0.893	0.214	1.169	-0.075	-0.085	1.170	0.516
Saint Lucia	-0.427	-1.293	-0.726	0.571	1.023	0.014	-0.478	0.201	0.516

Continuation of Table III

Country	GDP	PAV	URB	RPA	PRIM	POPD	EPPC	PHL	LL
Saint Vincent / Grenadines	-0.593	-0.527	-0.017	0.914	-0.323	0.045	-0.481	-0.057	0.516
Samoa	-0.527	-0.492	-1.393	-0.242	0.021	-0.147	-0.511	-0.677	0.516
San Marino	2.921	1.550	1.444	1.365	-0.177	0.175	-0.643	2.149	-1.927
Sao Tome and Principe	-0.781	0.593	-0.350	-0.224	0.452	-0.058	-0.620	-0.810	0.516
Saudi Arabia	0.260	-0.547	1.277	-0.343	-0.247	-0.186	0.560	-0.270	0.516
Senegal	-0.739	-0.571	-0.350	-0.343	0.059	-0.152	-0.614	-0.789	0.516
Seychelles	-0.072	1.085	0.359	-0.081	1.248	-0.054	-0.185	0.268	0.516
Sierra Leone	-0.859	-1.213	-0.768	-0.300	-0.046	-0.132	-0.633	-0.873	0.516
Singapore	1.823	1.550	1.861	1.819	4.082	4.996	0.792	1.179	0.516
Slovakia	0.360	1.151	0.067	-0.203	-0.696	-0.106	0.520	0.795	-1.927
Slovenia	0.859	1.547	-0.267	0.088	-0.247	-0.119	0.874	0.873	0.516
Solomon Islands	-0.726	-1.374	-1.477	-0.356	-0.838	-0.182	-0.628	-0.817	0.516
Somalia	-0.854	-1.096	-1.185	-0.362	-0.201	-0.186	-0.635	-0.894	0.516
South Africa	0.127	-0.841	0.067	-0.237	-0.790	-0.167	0.377	-0.351	0.516
Spain	1.180	1.520	0.943	-0.047	-0.571	-0.132	0.566	1.154	0.516
Sri Lanka	-0.554	1.400	-1.352	-0.296	-0.982	0.045	-0.565	-0.774	0.516
Sudan	-0.764	-0.361	-0.809	-0.377	-0.757	-0.184	-0.630	-0.843	0.516
Suriname	-0.527	-0.670	0.776	-0.365	2.015	-0.193	0.096	-0.199	0.516
Swaziland	-0.449	-0.604	-1.227	-0.273	-0.939	-0.143	-0.569	-0.732	-1.927
Sweden	1.823	0.902	1.152	-0.152	-0.060	-0.180	3.087	2.315	0.516
Switzerland	2.533	1.550	0.484	0.453	-0.397	-0.053	1.370	2.231	-1.927
Syrian Arab Republic	-0.560	-0.757	-0.183	-0.271	-0.529	-0.121	-0.380	-0.531	0.516
Tajikistan	-0.788	1.031	-1.143	-0.278	-0.633	-0.158	-0.157	-0.638	-1.927
Thailand	-0.183	1.475	-1.477	-0.318	-0.470	-0.098	-0.296	-0.469	0.516
The FYR of Macedonia	-0.427	0.464	0.150	-0.213	0.438	-0.130	0.070	0.046	-1.927
Togo	-0.748	-0.502	-0.934	-0.315	-0.601	-0.120	-0.638	-0.871	0.516
Tonga	-0.671	-0.640	-0.934	0.061	0.887	-0.081	-0.578	-0.536	0.516
Trinidad and Tobago	0.083	0.083	0.776	0.406	-0.955	-0.012	0.371	0.131	0.516
Tunisia	-0.183	0.494	0.442	-0.311	0.039	-0.147	-0.402	-0.578	0.516
Turkey	-0.172	-0.430	0.442	-0.142	-0.312	-0.126	-0.237	0.478	0.516

Continuation of Table III

Country	GDP	PAV	URB	RPA	PRIM	POPD	EPPC	PHL	LL
Turkmenistan	-0.394	1.004	-0.434	-0.357	-0.513	-0.188	-0.191	-0.527	-1.927
Tuvalu	-0.793	-1.449	-0.142	-0.016	1.172	0.146	-0.643	-0.463	0.516
Uganda	-0.781	-1.249	-1.727	-0.324	-0.920	-0.111	-0.628	-0.884	-1.927
Ukraine	-0.449	1.451	0.526	-0.160	-0.879	-0.131	0.131	0.031	0.516
United Arab Emirates	1.424	1.550	1.319	-0.351	1.274	-0.172	2.979	0.877	0.516
United Kingdom	1.823	1.550	1.402	0.355	-0.396	0.002	0.720	1.868	0.516
United Rep. of Tanzania	-0.847	-1.324	-0.976	-0.335	-0.827	-0.164	-0.626	-0.878	0.516
United States of America	3.109	0.314	0.901	-0.059	-0.853	-0.172	2.458	2.380	0.516
Uruguay	0.105	1.250	1.527	-0.355	1.181	-0.180	-0.134	0.405	0.516
Uzbekistan	-0.637	1.169	-0.768	-0.291	-0.689	-0.149	-0.248	-0.527	-1.927
Vanuatu	-0.770	-0.733	-1.393	-0.336	-0.103	-0.183	-0.597	-0.761	0.516
Venezuela	-0.238	-0.442	1.319	-0.328	-0.383	-0.174	0.118	-0.387	0.516
Vietnam	-0.682	-0.697	-1.310	-0.242	-0.999	0.003	-0.570	-0.742	0.516
Yemen	-0.824	-1.105	-1.268	-0.315	-0.658	-0.167	-0.603	-0.820	0.516
Yugoslavia	-0.665	0.419	-0.142	-0.149	-0.321	-0.112	0.066	0.002	0.516
Zambia	-0.818	-0.910	-0.642	-0.336	-0.151	-0.185	-0.463	-0.832	-1.927
Zimbabwe	-0.643	-0.028	-0.851	-0.356	-0.222	-0.172	-0.513	-0.806	-1.927

E. Table IV - Single Linkage Clustering for Standardized Data[65]

Country	8 Clusters	15 Clusters	Country	8 Clusters	15 Clusters
Afghanistan	1	1	Republic of Moldova	1	1
Armenia	1	1	Rwanda	1	1
Azerbaijan	1	1	Slovakia	1	1
Belarus	1	1	Swaziland	1	1
Bhutan	1	1	Tajikistan	1	1
Bolivia	1	1	The FYR of Macedonia	1	1
Botswana	1	1	Turkmenistan	1	1
Burkina Faso	1	1	Uganda	1	1
Burundi	1	1	Uzbekistan	1	1
Central African Republic	1	1	Zambia	1	1
Chad	1	1	Zimbabwe	1	1
Czech Republic	1	1	Austria	1	2
Ethiopia	1	1	Switzerland	1	2
Hungary	1	1	Paraguay	1	3
Kazakhstan	1	1	Andorra	1	4
Kyrgyzstan	1	1	Albania	1	5
Lao People's Dem. Rep.	1	1	Algeria	1	5
Lesotho	1	1	Angola	1	5
Malawi	1	1	Antigua and Barbuda	1	5
Mali	1	1	Argentina	1	5
Mongolia	1	1	Australia	1	5
Nepal	1	1	Bahamas	1	5
Niger	1	1	Bangladesh	1	5

[65] The countries are sorted according to their clusters.

Continuation of Table IV

Country	8 Clusters	15 Clusters	Country	8 Clusters	15 Clusters
Barbados	1	5	Ecuador	1	5
Belgium	1	5	Egypt	1	5
Belize	1	5	El Salvador	1	5
Benin	1	5	Equatorial Guinea	1	5
Bosnia and Herzegovina	1	5	Eritrea	1	5
Brazil	1	5	Estonia	1	5
Brunei Darussalam	1	5	Fiji	1	5
Bulgaria	1	5	France	1	5
Cambodia	1	5	French Guyana	1	5
Cameroon	1	5	French Polynesia	1	5
Cape Verde	1	5	Gabon	1	5
Chile	1	5	Gambia	1	5
China a	1	5	Georgia	1	5
Colombia	1	5	Germany	1	5
Comoros	1	5	Ghana	1	5
Congo, Republic	1	5	Greece	1	5
Costa Rica	1	5	Grenada	1	5
Cte d'Ivoire	1	5	Guadeloupe	1	5
Croatia	1	5	Guatemala	1	5
Cuba	1	5	Guinea	1	5
Dem. Republic of Congo	1	5	Guinea-Bissau	1	5
Denmark	1	5	Guyana	1	5
Djibouti	1	5	Haiti	1	5
Dominica	1	5	Honduras	1	5
Dominican Republic	1	5	India	1	5

Continuation of Table IV

Country	**8 Clusters**	**15 Clusters**	**Country**	**8 Clusters**	**15 Clusters**
Indonesia	1	5	Mozambique	1	5
Iran (Islamic Rep. of)	1	5	Myanmar	1	5
Iraq	1	5	Namibia	1	5
Ireland	1	5	Nauru	1	5
Israel	1	5	Netherlands	1	5
Italy	1	5	Netherlands Antilles	1	5
Jamaica	1	5	New Caledonia	1	5
Japan	1	5	New Zealand	1	5
Jordan	1	5	Nicaragua	1	5
Kenya	1	5	Nigeria	1	5
Korea, Dem. People's Rep. of	1	5	Oman	1	5
Korea, Republic of	1	5	Pakistan	1	5
Latvia	1	5	Palau	1	5
Lebanon	1	5	Panama	1	5
Liberia	1	5	Papua New Guinea	1	5
Libyan Arab Jamahiriya	1	5	Peru	1	5
Lithuania	1	5	Philippines	1	5
Madagascar	1	5	Poland	1	5
Malaysia	1	5	Portugal	1	5
Malta	1	5	Puerto Rico	1	5
Mauritania	1	5	Reunion	1	5
Mauritius	1	5	Romania	1	5
Mexico	1	5	Russian Federation	1	5
Micronesia, Fed. States of	1	5	Saint Kitts and Nevis	1	5
Morocco	1	5	Saint Lucia	1	5

Continuation of Table IV

Country	**8 Clusters**	**15 Clusters**	**Country**	**8 Clusters**	**15 Clusters**
Saint Vincent / Grenadines	1	5	United Rep. of Tanzania	1	5
Samoa	1	5	Uruguay	1	5
Sao Tome and Principe	1	5	Vanuatu	1	5
Saudi Arabia	1	5	Venezuela	1	5
Senegal	1	5	Vietnam	1	5
Seychelles	1	5	Yemen	1	5
Sierra Leone	1	5	Yugoslavia	1	5
Slovenia	1	5	Canada	1	6
Solomon Islands	1	5	Finland	1	6
Somalia	1	5	Sweden	1	6
South Africa	1	5	United States of America	1	6
Spain	1	5	Kuwait	1	7
Sri Lanka	1	5	Qatar	1	7
Sudan	1	5	United Arab Emirates	1	7
Suriname	1	5	Bahrain	1	8
Syrian Arab Republic	1	5	Luxembourg	2	9
Thailand	1	5	San Marino	2	9
Togo	1	5	Liechtenstein	3	10
Tonga	1	5	Bermuda	4	11
Trinidad and Tobago	1	5	Iceland	5	12
Tunisia	1	5	Norway	6	13
Turkey	1	5	Singapore	7	14
Tuvalu	1	5	Monaco	8	15
Ukraine	1	5			
United Kingdom	1	5			

F. Table V - Ward Clustering of Standardized Data

Country	8 Clusters	9 Clusters	10 Clusters	Country	8 Clusters	9 Clusters	10 Clusters
Afghanistan	1	1	1	Bhutan	2	2	2
Bolivia	1	1	1	Botswana	2	2	2
Burkina Faso	1	1	1	Czech Republic	2	2	2
Burundi	1	1	1	Hungary	2	2	2
Central African Republic	1	1	1	Kazakhstan	2	2	2
Chad	1	1	1	Kyrgyzstan	2	2	2
Ethiopia	1	1	1	Republic of Moldova	2	2	2
Lao People's Dem. Rep.	1	1	1	Slovakia	2	2	2
Lesotho	1	1	1	Tajikistan	2	2	2
Malawi	1	1	1	The FYR of Macedonia	2	2	2
Mali	1	1	1	Turkmenistan	2	2	2
Mongolia	1	1	1	Uzbekistan	2	2	2
Nepal	1	1	1	Zimbabwe	2	2	2
Niger	1	1	1	Albania	3	3	3
Paraguay	1	1	1	Angola	3	3	3
Rwanda	1	1	1	Bangladesh	3	3	3
Swaziland	1	1	1	Belize	3	3	3
Uganda	1	1	1	Benin	3	3	3
Zambia	1	1	1	Bosnia and Herzegovina	3	3	3
Andorra	2	2	2	Cambodia	3	3	3
Armenia	2	2	2	China a	3	3	3
Azerbaijan	2	2	2	Cte d'Ivoire	3	3	3
Belarus	2	2	2	Dem. Republic of Congo	3	3	3

Continuation of Table V

Country	**8 Clusters**	**9 Clusters**	**10 Clusters**	**Country**	**8 Clusters**	**9 Clusters**	**10 Clusters**
Eritrea	3	3	3	Togo	3	3	3
Gambia	3	3	3	United Rep. of Tanzania	3	3	3
Ghana	3	3	3	Vanuatu	3	3	3
Grenada	3	3	3	Vietnam	3	3	3
Guinea	3	3	3	Yemen	3	3	3
Guinea-Bissau	3	3	3	Algeria	4	4	4
Guyana	3	3	3	Bulgaria	4	4	4
Haiti	3	3	3	Cape Verde	4	4	4
India	3	3	3	Comoros	4	4	4
Indonesia	3	3	3	Croatia	4	4	4
Kenya	3	3	3	Cuba	4	4	4
Madagascar	3	3	3	Egypt	4	4	4
Micronesia, Fed. States of	3	3	3	Fiji	4	4	4
Mozambique	3	3	3	French Polynesia	4	4	4
Myanmar	3	3	3	Georgia	4	4	4
Namibia	3	3	3	Guatemala	4	4	4
Nigeria	3	3	3	Iran (Islamic Rep. of)	4	4	4
Pakistan	3	3	3	Iraq	4	4	4
Papua New Guinea	3	3	3	Jordan	4	4	4
Saint Vincent / Grenadines	3	3	3	Lithuania	4	4	4
Samoa	3	3	3	Malaysia	4	4	4
Sierra Leone	3	3	3	Mauritius	4	4	4
Solomon Islands	3	3	3	Morocco	4	4	4
Somalia	3	3	3	Poland	4	4	4
Sudan	3	3	3	Romania	4	4	4

Continuation of Table V

Country	**8 Clusters**	**9 Clusters**	**10 Clusters**	**Country**	**8 Clusters**	**9 Clusters**	**10 Clusters**
Russian Federation	4	4	4	Libyan Arab Jamahiriya	4	5	5
Sao Tome and Principe	4	4	4	Mauritania	4	5	5
Senegal	4	4	4	Mexico	4	5	5
Sri Lanka	4	4	4	Nicaragua	4	5	5
Thailand	4	4	4	Oman	4	5	5
Trinidad and Tobago	4	4	4	Peru	4	5	5
Tunisia	4	4	4	Philippines	4	5	5
Ukraine	4	4	4	Reunion	4	5	5
Yugoslavia	4	4	4	Saudi Arabia	4	5	5
Brazil	4	5	5	South Africa	4	5	5
Brunei Darussalam	4	5	5	Syrian Arab Republic	4	5	5
Cameroon	4	5	5	Turkey	4	5	5
Colombia	4	5	5	Venezuela	4	5	5
Congo, Republic	4	5	5	Antigua and Barbuda	5	6	6
Costa Rica	4	5	5	Argentina	5	6	6
Dominica	4	5	5	Bahamas	5	6	6
Ecuador	4	5	5	Chile	5	6	6
El Salvador	4	5	5	Djibouti	5	6	6
Equatorial Guinea	4	5	5	Dominican Republic	5	6	6
Estonia	4	5	5	Gabon	5	6	6
French Guyana	4	5	5	Jamaica	5	6	6
Guadeloupe	4	5	5	Lebanon	5	6	6
Honduras	4	5	5	Liberia	5	6	6
Korea, Dem. People's Rep. of	4	5	5	Nauru	5	6	6
Latvia	4	5	5	Netherlands Antilles	5	6	6

Continuation of Table V

Country	**8 Clusters**	**9 Clusters**	**10 Clusters**	**Country**	**8 Clusters**	**9 Clusters**	**10 Clusters**
New Caledonia	5	6	6	Netherlands	6	7	7
Palau	5	6	6	New Zealand	6	7	7
Panama	5	6	6	Portugal	6	7	7
Saint Kitts and Nevis	5	6	6	Puerto Rico	6	7	7
Saint Lucia	5	6	6	Slovenia	6	7	7
Seychelles	5	6	6	Spain	6	7	7
Suriname	5	6	6	United Kingdom	6	7	7
Tonga	5	6	6	Austria	6	7	8
Tuvalu	5	6	6	Liechtenstein	6	7	8
Uruguay	5	6	6	Luxembourg	6	7	8
Australia	6	7	7	San Marino	6	7	8
Bahrain	6	7	7	Switzerland	6	7	8
Barbados	6	7	7	Canada	7	8	9
Belgium	6	7	7	Finland	7	8	9
Bermuda	6	7	7	Iceland	7	8	9
Denmark	6	7	7	Kuwait	7	8	9
France	6	7	7	Norway	7	8	9
Germany	6	7	7	Qatar	7	8	9
Greece	6	7	7	Singapore	7	8	9
Ireland	6	7	7	Sweden	7	8	9
Israel	6	7	7	United Arab Emirates	7	8	9
Italy	6	7	7	United States of America	7	8	9
Japan	6	7	7	Monaco	8	9	10
Korea, Republic of	6	7	7				
Malta	6	7	7				

G. Table VI - Ward Clustering of Standardized Data Omitting Monaco

Country	8 Clusters	9 Clusters	10 Clusters	11 Clusters	12 Clusters	15 Clusters
Afghanistan	1	1	1	1	1	1
Bolivia	1	1	1	1	1	1
Burkina Faso	1	1	1	1	1	1
Burundi	1	1	1	1	1	1
Central African Republic	1	1	1	1	1	1
Chad	1	1	1	1	1	1
Ethiopia	1	1	1	1	1	1
Lao People's Dem. Rep.	1	1	1	1	1	1
Lesotho	1	1	1	1	1	1
Malawi	1	1	1	1	1	1
Mali	1	1	1	1	1	1
Mongolia	1	1	1	1	1	1
Nepal	1	1	1	1	1	1
Niger	1	1	1	1	1	1
Paraguay	1	1	1	1	1	1
Rwanda	1	1	1	1	1	1
Swaziland	1	1	1	1	1	1
Uganda	1	1	1	1	1	1
Zambia	1	1	1	1	1	1
Andorra	2	2	2	2	2	2
Armenia	2	2	2	2	2	2
Belarus	2	2	2	2	2	2
Czech Republic	2	2	2	2	2	2

Continuation of Table VI

Country	**8 Clusters**	**9 Clusters**	**10 Clusters**	**11 Clusters**	**12 Clusters**	**15 Clusters**
Hungary	2	2	2	2	2	2
Slovakia	2	2	2	2	2	2
The FYR of Macedonia	2	2	2	2	2	2
Azerbaijan	2	2	2	2	2	3
Bhutan	2	2	2	2	2	3
Botswana	2	2	2	2	2	3
Kazakhstan	2	2	2	2	2	3
Kyrgyzstan	2	2	2	2	2	3
Republic of Moldova	2	2	2	2	2	3
Tajikistan	2	2	2	2	2	3
Turkmenistan	2	2	2	2	2	3
Uzbekistan	2	2	2	2	2	3
Zimbabwe	2	2	2	2	2	3
Albania	3	3	3	3	3	4
Angola	3	3	3	3	3	4
Belize	3	3	3	3	3	4
Benin	3	3	3	3	3	4
Bosnia and Herzegovina	3	3	3	3	3	4
Cambodia	3	3	3	3	3	4
Cameroon	3	3	3	3	3	4
China	3	3	3	3	3	4
Cte d'Ivoire	3	3	3	3	3	4
Dem. Republic of Congo	3	3	3	3	3	4
Equatorial Guinea	3	3	3	3	3	4
Eritrea	3	3	3	3	3	4

Continuation of Table VI

Country	**8 Clusters**	**9 Clusters**	**10 Clusters**	**11 Clusters**	**12 Clusters**	**15 Clusters**
Ghana	3	3	3	3	3	4
Guinea	3	3	3	3	3	4
Guinea-Bissau	3	3	3	3	3	4
Guyana	3	3	3	3	3	4
Haiti	3	3	3	3	3	4
India	3	3	3	3	3	4
Indonesia	3	3	3	3	3	4
Kenya	3	3	3	3	3	4
Madagascar	3	3	3	3	3	4
Micronesia, Fed. States of	3	3	3	3	3	4
Mozambique	3	3	3	3	3	4
Myanmar	3	3	3	3	3	4
Namibia	3	3	3	3	3	4
Nigeria	3	3	3	3	3	4
Pakistan	3	3	3	3	3	4
Papua New Guinea	3	3	3	3	3	4
Samoa	3	3	3	3	3	4
Sierra Leone	3	3	3	3	3	4
Solomon Islands	3	3	3	3	3	4
Somalia	3	3	3	3	3	4
Sudan	3	3	3	3	3	4
Togo	3	3	3	3	3	4
United Rep. of Tanzania	3	3	3	3	3	4
Vanuatu	3	3	3	3	3	4
Vietnam	3	3	3	3	3	4

Continuation of Table VI

Country	8 Clusters	9 Clusters	10 Clusters	11 Clusters	12 Clusters	15 Clusters
Yemen	3	3	3	3	3	4
Algeria	4	4	4	4	4	5
Cape Verde	4	4	4	4	4	5
Comoros	4	4	4	4	4	5
Cuba	4	4	4	4	4	5
Egypt	4	4	4	4	4	5
Fiji	4	4	4	4	4	5
French Polynesia	4	4	4	4	4	5
Georgia	4	4	4	4	4	5
Guatemala	4	4	4	4	4	5
Iran (Islamic Rep. of)	4	4	4	4	4	5
Iraq	4	4	4	4	4	5
Jordan	4	4	4	4	4	5
Malaysia	4	4	4	4	4	5
Mauritius	4	4	4	4	4	5
Morocco	4	4	4	4	4	5
Romania	4	4	4	4	4	5
Russian Federation	4	4	4	4	4	5
Sao Tome and Principe	4	4	4	4	4	5
Senegal	4	4	4	4	4	5
Sri Lanka	4	4	4	4	4	5
Thailand	4	4	4	4	4	5
Tunisia	4	4	4	4	4	5
Ukraine	4	4	4	4	4	5
Yugoslavia	4	4	4	4	4	5

Continuation of Table VI

Country	**8 Clusters**	**9 Clusters**	**10 Clusters**	**11 Clusters**	**12 Clusters**	**15 Clusters**
Antigua and Barbuda	4	4	5	5	5	6
Bangladesh	4	4	5	5	5	6
Gambia	4	4	5	5	5	6
Grenada	4	4	5	5	5	6
Liberia	4	4	5	5	5	6
Saint Kitts and Nevis	4	4	5	5	5	6
Saint Lucia	4	4	5	5	5	6
Saint Vincent / Grenadines	4	4	5	5	5	6
Tonga	4	4	5	5	5	6
Tuvalu	4	4	5	5	5	6
Brazil	4	4	5	6	6	7
Brunei Darussalam	4	4	5	6	6	7
Colombia	4	4	5	6	6	7
Dominica	4	4	5	6	6	7
Estonia	4	4	5	6	6	7
French Guyana	4	4	5	6	6	7
Guadeloupe	4	4	5	6	6	7
Latvia	4	4	5	6	6	7
Libyan Arab Jamahiriya	4	4	5	6	6	7
Mexico	4	4	5	6	6	7
Oman	4	4	5	6	6	7
Poland	4	4	5	6	6	7
Reunion	4	4	5	6	6	7
Saudi Arabia	4	4	5	6	6	7
South Africa	4	4	5	6	6	7

Continuation of Table VI

Country	**8 Clusters**	**9 Clusters**	**10 Clusters**	**11 Clusters**	**12 Clusters**	**15 Clusters**
Trinidad and Tobago	4	4	5	6	6	7
Turkey	4	4	5	6	6	7
Venezuela	4	4	5	6	6	7
Congo, Republic	4	4	5	6	6	8
Costa Rica	4	4	5	6	6	8
Ecuador	4	4	5	6	6	8
El Salvador	4	4	5	6	6	8
Honduras	4	4	5	6	6	8
Korea, Dem. People's Rep. of	4	4	5	6	6	8
Mauritania	4	4	5	6	6	8
Nicaragua	4	4	5	6	6	8
Peru	4	4	5	6	6	8
Philippines	4	4	5	6	6	8
Syrian Arab Republic	4	4	5	6	6	8
Argentina	5	5	6	7	7	9
Bahamas	5	5	6	7	7	9
Chile	5	5	6	7	7	9
Djibouti	5	5	6	7	7	9
Dominican Republic	5	5	6	7	7	9
Gabon	5	5	6	7	7	9
Jamaica	5	5	6	7	7	9
Lebanon	5	5	6	7	7	9
Nauru	5	5	6	7	7	9
Netherlands Antilles	5	5	6	7	7	9
New Caledonia	5	5	6	7	7	9

Continuation of Table VI

Country	8 Clusters	9 Clusters	10 Clusters	11 Clusters	12 Clusters	15 Clusters
Palau	5	5	6	7	7	9
Panama	5	5	6	7	7	9
Puerto Rico	5	5	6	7	7	9
Seychelles	5	5	6	7	7	9
Suriname	5	5	6	7	7	9
Uruguay	5	5	6	7	7	9
Australia	6	6	7	8	8	10
Canada	6	6	7	8	8	10
Finland	6	6	7	8	8	10
Iceland	6	6	7	8	8	10
Kuwait	6	6	7	8	8	10
New Zealand	6	6	7	8	8	10
Norway	6	6	7	8	8	10
Qatar	6	6	7	8	8	10
Sweden	6	6	7	8	8	10
United Arab Emirates	6	6	7	8	8	10
United States of America	6	6	7	8	8	10
Austria	7	7	8	9	9	11
Liechtenstein	7	7	8	9	9	11
Luxembourg	7	7	8	9	9	11
San Marino	7	7	8	9	9	11
Switzerland	7	7	8	9	9	11
Bulgaria	7	7	8	9	10	12
Croatia	7	7	8	9	10	12
Greece	7	7	8	9	10	12

Continuation of Table VI

Country	**8 Clusters**	**9 Clusters**	**10 Clusters**	**11 Clusters**	**12 Clusters**	**15 Clusters**
Ireland	7	7	8	9	10	12
Israel	7	7	8	9	10	12
Korea, Republic of	7	7	8	9	10	12
Lithuania	7	7	8	9	10	12
Portugal	7	7	8	9	10	12
Slovenia	7	7	8	9	10	12
Spain	7	7	8	9	10	12
Denmark	7	7	8	9	10	13
France	7	7	8	9	10	13
Germany	7	7	8	9	10	13
Italy	7	7	8	9	10	13
Netherlands	7	7	8	9	10	13
United Kingdom	7	7	8	9	10	13
Bahrain	7	8	9	10	11	14
Barbados	7	8	9	10	11	14
Belgium	7	8	9	10	11	14
Bermuda	7	8	9	10	11	14
Japan	7	8	9	10	11	14
Malta	7	8	9	10	11	14
Singapore	8	9	10	11	12	15

H. Table VII - Ward Clustering of Standardized Data Omitting Monaco and Singapore

Country / No. of Clusters	4	5	6	7	8	9	10	11	12	15
Afghanistan	1	1	1	1	1	1	1	1	1	1
Bolivia	1	1	1	1	1	1	1	1	1	1
Burkina Faso	1	1	1	1	1	1	1	1	1	1
Burundi	1	1	1	1	1	1	1	1	1	1
Central African Republic	1	1	1	1	1	1	1	1	1	1
Chad	1	1	1	1	1	1	1	1	1	1
Ethiopia	1	1	1	1	1	1	1	1	1	1
Lao People's Dem. Rep.	1	1	1	1	1	1	1	1	1	1
Lesotho	1	1	1	1	1	1	1	1	1	1
Malawi	1	1	1	1	1	1	1	1	1	1
Mali	1	1	1	1	1	1	1	1	1	1
Mongolia	1	1	1	1	1	1	1	1	1	1
Nepal	1	1	1	1	1	1	1	1	1	1
Niger	1	1	1	1	1	1	1	1	1	1
Paraguay	1	1	1	1	1	1	1	1	1	1
Rwanda	1	1	1	1	1	1	1	1	1	1
Swaziland	1	1	1	1	1	1	1	1	1	1
Uganda	1	1	1	1	1	1	1	1	1	1
Zambia	1	1	1	1	1	1	1	1	1	1
Armenia	1	1	1	2	2	2	2	2	2	2
Azerbaijan	1	1	1	2	2	2	2	2	2	2
Belarus	1	1	1	2	2	2	2	2	2	2
Bhutan	1	1	1	2	2	2	2	2	2	2
Botswana	1	1	1	2	2	2	2	2	2	2
Kazakhstan	1	1	1	2	2	2	2	2	2	2
Kyrgyzstan	1	1	1	2	2	2	2	2	2	2
Republic of Moldova	1	1	1	2	2	2	2	2	2	2
Tajikistan	1	1	1	2	2	2	2	2	2	2

Continuation of Table VII

Country / No. of Clusters	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**15**
The FYR of Macedonia	1	1	1	2	2	2	2	2	2	2
Turkmenistan	1	1	1	2	2	2	2	2	2	2
Uzbekistan	1	1	1	2	2	2	2	2	2	2
Zimbabwe	1	1	1	2	2	2	2	2	2	2
Albania	2	2	2	3	3	3	3	3	3	3
Bosnia and Herzegovina	2	2	2	3	3	3	3	3	3	3
Comoros	2	2	2	3	3	3	3	3	3	3
Ghana	2	2	2	3	3	3	3	3	3	3
Haiti	2	2	2	3	3	3	3	3	3	3
India	2	2	2	3	3	3	3	3	3	3
Indonesia	2	2	2	3	3	3	3	3	3	3
Micronesia, Fed. States of	2	2	2	3	3	3	3	3	3	3
Nigeria	2	2	2	3	3	3	3	3	3	3
Pakistan	2	2	2	3	3	3	3	3	3	3
Sri Lanka	2	2	2	3	3	3	3	3	3	3
Sudan	2	2	2	3	3	3	3	3	3	3
Thailand	2	2	2	3	3	3	3	3	3	3
Togo	2	2	2	3	3	3	3	3	3	3
Vietnam	2	2	2	3	3	3	3	3	3	3
Angola	2	2	2	3	3	3	3	3	3	4
Cambodia	2	2	2	3	3	3	3	3	3	4
Cte d'Ivoire	2	2	2	3	3	3	3	3	3	4
Dem. Republic of Congo	2	2	2	3	3	3	3	3	3	4
Eritrea	2	2	2	3	3	3	3	3	3	4
Guinea	2	2	2	3	3	3	3	3	3	4
Guinea-Bissau	2	2	2	3	3	3	3	3	3	4
Guyana	2	2	2	3	3	3	3	3	3	4
Kenya	2	2	2	3	3	3	3	3	3	4
Madagascar	2	2	2	3	3	3	3	3	3	4
Mozambique	2	2	2	3	3	3	3	3	3	4

Continuation of Table VII

Country / No. of Clusters	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**15**
Myanmar	2	2	2	3	3	3	3	3	3	4
Namibia	2	2	2	3	3	3	3	3	3	4
Papua New Guinea	2	2	2	3	3	3	3	3	3	4
Samoa	2	2	2	3	3	3	3	3	3	4
Sierra Leone	2	2	2	3	3	3	3	3	3	4
Solomon Islands	2	2	2	3	3	3	3	3	3	4
Somalia	2	2	2	3	3	3	3	3	3	4
United Rep. of Tanzania	2	2	2	3	3	3	3	3	3	4
Vanuatu	2	2	2	3	3	3	3	3	3	4
Yemen	2	2	2	3	3	3	3	3	3	4
Belize	2	2	2	3	3	3	3	3	3	5
Benin	2	2	2	3	3	3	3	3	3	5
Cameroon	2	2	2	3	3	3	3	3	3	5
China	2	2	2	3	3	3	3	3	3	5
Congo, Republic	2	2	2	3	3	3	3	3	3	5
Costa Rica	2	2	2	3	3	3	3	3	3	5
Ecuador	2	2	2	3	3	3	3	3	3	5
Equatorial Guinea	2	2	2	3	3	3	3	3	3	5
Fiji	2	2	2	3	3	3	3	3	3	5
Guatemala	2	2	2	3	3	3	3	3	3	5
Honduras	2	2	2	3	3	3	3	3	3	5
Korea, Dem. People's Rep. of	2	2	2	3	3	3	3	3	3	5
Mauritania	2	2	2	3	3	3	3	3	3	5
Nicaragua	2	2	2	3	3	3	3	3	3	5
Peru	2	2	2	3	3	3	3	3	3	5
Senegal	2	2	2	3	3	3	3	3	3	5
Syrian Arab Republic	2	2	2	3	3	3	3	3	3	5
Algeria	3	3	3	4	4	4	4	4	4	6
Brazil	3	3	3	4	4	4	4	4	4	6
Brunei Darussalam	3	3	3	4	4	4	4	4	4	6

Continuation of Table VII

Country / No. of Clusters	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**15**
Colombia	3	3	3	4	4	4	4	4	4	6
Egypt	3	3	3	4	4	4	4	4	4	6
French Polynesia	3	3	3	4	4	4	4	4	4	6
Iran (Islamic Rep. of)	3	3	3	4	4	4	4	4	4	6
Libyan Arab Jamahiriya	3	3	3	4	4	4	4	4	4	6
Malaysia	3	3	3	4	4	4	4	4	4	6
Mexico	3	3	3	4	4	4	4	4	4	6
Morocco	3	3	3	4	4	4	4	4	4	6
Oman	3	3	3	4	4	4	4	4	4	6
Romania	3	3	3	4	4	4	4	4	4	6
Russian Federation	3	3	3	4	4	4	4	4	4	6
Saudi Arabia	3	3	3	4	4	4	4	4	4	6
South Africa	3	3	3	4	4	4	4	4	4	6
Turkey	3	3	3	4	4	4	4	4	4	6
Ukraine	3	3	3	4	4	4	4	4	4	6
Venezuela	3	3	3	4	4	4	4	4	4	6
Yugoslavia	3	3	3	4	4	4	4	4	4	6
Cape Verde	3	3	3	4	4	4	4	4	4	7
Cuba	3	3	3	4	4	4	4	4	4	7
Georgia	3	3	3	4	4	4	4	4	4	7
Iraq	3	3	3	4	4	4	4	4	4	7
Jamaica	3	3	3	4	4	4	4	4	4	7
Jordan	3	3	3	4	4	4	4	4	4	7
Sao Tome and Principe	3	3	3	4	4	4	4	4	4	7
Seychelles	3	3	3	4	4	4	4	4	4	7
Tunisia	3	3	3	4	4	4	4	4	4	7
Uruguay	3	3	3	4	4	4	4	4	4	7
Bangladesh	3	3	3	4	4	4	5	5	5	8
Barbados	3	3	3	4	4	4	5	5	5	8
Gambia	3	3	3	4	4	4	5	5	5	8

Continuation of Table VII

Country / No. of Clusters	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**15**
Grenada	3	3	3	4	4	4	5	5	5	8
Guadeloupe	3	3	3	4	4	4	5	5	5	8
Mauritius	3	3	3	4	4	4	5	5	5	8
Poland	3	3	3	4	4	4	5	5	5	8
Reunion	3	3	3	4	4	4	5	5	5	8
Saint Vincent / Grenadines	3	3	3	4	4	4	5	5	5	8
Trinidad and Tobago	3	3	3	4	4	4	5	5	5	8
Antigua and Barbuda	3	3	3	4	4	5	6	6	6	9
Argentina	3	3	3	4	4	5	6	6	6	9
Chile	3	3	3	4	4	5	6	6	6	9
Djibouti	3	3	3	4	4	5	6	6	6	9
Dominica	3	3	3	4	4	5	6	6	6	9
Dominican Republic	3	3	3	4	4	5	6	6	6	9
El Salvador	3	3	3	4	4	5	6	6	6	9
Estonia	3	3	3	4	4	5	6	6	6	9
French Guyana	3	3	3	4	4	5	6	6	6	9
Gabon	3	3	3	4	4	5	6	6	6	9
Latvia	3	3	3	4	4	5	6	6	6	9
Liberia	3	3	3	4	4	5	6	6	6	9
Panama	3	3	3	4	4	5	6	6	6	9
Philippines	3	3	3	4	4	5	6	6	6	9
Saint Kitts and Nevis	3	3	3	4	4	5	6	6	6	9
Saint Lucia	3	3	3	4	4	5	6	6	6	9
Suriname	3	3	3	4	4	5	6	6	6	9
Tonga	3	3	3	4	4	5	6	6	6	9
Tuvalu	3	3	3	4	4	5	6	6	6	9
Andorra	4	4	4	5	5	6	7	7	7	10
Austria	4	4	4	5	5	6	7	7	7	10
Czech Republic	4	4	4	5	5	6	7	7	7	10
Hungary	4	4	4	5	5	6	7	7	7	10

Continuation of Table VII

Country / No. of Clusters	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**15**
Liechtenstein	4	4	4	5	5	6	7	7	7	10
Luxembourg	4	4	4	5	5	6	7	7	7	10
San Marino	4	4	4	5	5	6	7	7	7	10
Slovakia	4	4	4	5	5	6	7	7	7	10
Switzerland	4	4	4	5	5	6	7	7	7	10
Belgium	4	4	4	5	5	6	7	8	8	11
Denmark	4	4	4	5	5	6	7	8	8	11
France	4	4	4	5	5	6	7	8	8	11
Germany	4	4	4	5	5	6	7	8	8	11
Italy	4	4	4	5	5	6	7	8	8	11
Japan	4	4	4	5	5	6	7	8	8	11
Netherlands	4	4	4	5	5	6	7	8	8	11
United Kingdom	4	4	4	5	5	6	7	8	8	11
Bulgaria	4	4	4	5	5	6	7	8	9	12
Croatia	4	4	4	5	5	6	7	8	9	12
Greece	4	4	4	5	5	6	7	8	9	12
Ireland	4	4	4	5	5	6	7	8	9	12
Lithuania	4	4	4	5	5	6	7	8	9	12
Portugal	4	4	4	5	5	6	7	8	9	12
Slovenia	4	4	4	5	5	6	7	8	9	12
Spain	4	4	4	5	5	6	7	8	9	12
Australia	4	4	5	6	6	7	8	9	10	13
Canada	4	4	5	6	6	7	8	9	10	13
Finland	4	4	5	6	6	7	8	9	10	13
Iceland	4	4	5	6	6	7	8	9	10	13
New Zealand	4	4	5	6	6	7	8	9	10	13
Norway	4	4	5	6	6	7	8	9	10	13
Sweden	4	4	5	6	6	7	8	9	10	13
United States of America	4	4	5	6	6	7	8	9	10	13
Bahamas	4	4	5	6	7	8	9	10	11	14

Continuation of Table VII

Country / No. of Clusters	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**15**
Israel	4	4	5	6	7	8	9	10	11	14
Korea, Republic of	4	4	5	6	7	8	9	10	11	14
Kuwait	4	4	5	6	7	8	9	10	11	14
Lebanon	4	4	5	6	7	8	9	10	11	14
Nauru	4	4	5	6	7	8	9	10	11	14
Netherlands Antilles	4	4	5	6	7	8	9	10	11	14
New Caledonia	4	4	5	6	7	8	9	10	11	14
Palau	4	4	5	6	7	8	9	10	11	14
Puerto Rico	4	4	5	6	7	8	9	10	11	14
Qatar	4	4	5	6	7	8	9	10	11	14
United Arab Emirates	4	4	5	6	7	8	9	10	11	14
Bahrain	4	5	6	7	8	9	10	11	12	15
Bermuda	4	5	6	7	8	9	10	11	12	15
Malta	4	5	6	7	8	9	10	11	12	15

I. Table VIII - Clusters obtained by *Ward* Method and Country's Category[66]

Country	8 Cl.	15 Cl.	Cat.	Country	8 Cl.	15 Cl.	Cat.
Afghanistan	1	1	LLDC	Azerbaijan	2	2	USSR/EE
Bolivia	1	1	LDC	Belarus	2	2	USSR/EE
Burkina Faso	1	1	LLDC	Bhutan	2	2	LLDC
Burundi	1	1	LLDC	Botswana	2	2	LLDC
Central African Republic	1	1	LLDC	Kazakhstan	2	2	USSR/EE
Chad	1	1	LLDC	Kyrgyzstan	2	2	USSR/EE
Ethiopia	1	1	LLDC	Republic of Moldova	2	2	USSR/EE
Lao People's Dem. Rep.	1	1	LLDC	Tajikistan	2	2	USSR/EE
Lesotho	1	1	LLDC	The FYR of Macedonia	2	2	USSR/EE
Malawi	1	1	LLDC	Turkmenistan	2	2	USSR/EE
Mali	1	1	LLDC	Uzbekistan	2	2	USSR/EE
Mongolia	1	1	LDC	Zimbabwe	2	2	
Nepal	1	1	LLDC	Albania	3	3	USSR/EE
Niger	1	1	LLDC	Bosnia and Herzegovina	3	3	USSR/EE
Paraguay	1	1	LDC	Comoros	3	3	LLDC
Rwanda	1	1	LLDC	Ghana	3	3	LDC
Swaziland	1	1	LDC	Haiti	3	3	LLDC
Uganda	1	1	LLDC	India	3	3	LDC
Zambia	1	1		Indonesia	3	3	LDC
Armenia	2	2	USSR/EE	Micronesia, Fed. States of	3	3	LDC

[66] To give a reference point, the official category a country belongs to according to UN statistics is included in the table.

Continuation of Table VIII

Country	**8 Cl.**	**15 Cl.**	**Cat.**	**Country**	**8 Cl.**	**15 Cl.**	**Cat.**
Nigeria	3	3	LDC	United Rep. of Tanzania	3	4	LLDC
Pakistan	3	3	LDC	Vanuatu	3	4	LLDC
Sri Lanka	3	3	LDC	Yemen	3	4	LLDC
Sudan	3	3	LLDC	Belize	3	5	LDC
Thailand	3	3	LDC	Benin	3	5	LLDC
Togo	3	3	LLDC	Cameroon	3	5	LDC
Vietnam	3	3	LDC	China	3	5	LDC
Angola	3	4	LDC	Congo, Republic	3	5	LDC
Cambodia	3	4	LDC	Costa Rica	3	5	LDC
Cte d'Ivoire	3	4	LDC	Ecuador	3	5	LDC
Dem. Republic of Congo	3	4	LDC	Equatorial Guinea	3	5	LLDC
Eritrea	3	4	LLDC	Fiji	3	5	LDC
Guinea	3	4	LLDC	Guatemala	3	5	LDC
Guinea-Bissau	3	4	LLDC	Honduras	3	5	LDC
Guyana	3	4	LDC	Korea, Dem. People's Rep. of	3	5	LDC
Kenya	3	4	LDC	Mauritania	3	5	LLDC
Madagascar	3	4	LDC	Nicaragua	3	5	LDC
Mozambique	3	4	LLDC	Peru	3	5	LDC
Myanmar	3	4	LLDC	Senegal	3	5	LDC
Namibia	3	4	LDC	Syrian Arab Republic	3	5	LDC
Papua New Guinea	3	4	LDC	Algeria	4	6	LDC
Samoa	3	4	LLDC	Brazil	4	6	LDC
Sierra Leone	3	4	LLDC	Brunei Darussalam	4	6	LDC
Solomon Islands	3	4	LDC	Colombia	4	6	LDC
Somalia	3	4	LLDC	Egypt	4	6	LDC

Continuation of Table VIII

Country	8 Cl.	15 Cl.	Cat.	Country	8 Cl.	15 Cl.	Cat.
French Polynesia	4	6	LDC	Bangladesh	4	8	LLDC
Iran (Islamic Rep. of)	4	6	LDC	Barbados	4	8	LDC
Libyan Arab Jamahiriya	4	6	LDC	Gambia	4	8	LLDC
Malaysia	4	6	LDC	Grenada	4	8	LDC
Mexico	4	6	OECD	Guadeloupe	4	8	LDC
Morocco	4	6	LDC	Mauritius	4	8	LDC
Oman	4	6	LDC	Poland	4	8	*USSR/EE OECD*
Romania	4	6	USSR/EE	Reunion	4	8	LDC
Russian Federation	4	6	USSR/EE	Saint Vincent / Grenadines	4	8	LDC
Saudi Arabia	4	6	LDC	Trinidad and Tobago	4	8	LDC
South Africa	4	6		Antigua and Barbuda	4	9	LDC
Turkey	4	6	OECD	Argentina	4	9	LDC
Ukraine	4	6	USSR/EE	Chile	4	9	LDC
Venezuela	4	6	LDC	Djibouti	4	9	LLDC
Yugoslavia	4	6		Dominica	4	9	LDC
Cape Verde	4	7	LLDC	Dominican Republic	4	9	LDC
Cuba	4	7	LDC	El Salvador	4	9	LDC
Georgia	4	7	USSR/EE	Estonia	4	9	USSR/EE
Iraq	4	7	LDC	French Guyana	4	9	LDC
Jamaica	4	7	LDC	Gabon	4	9	LDC
Jordan	4	7	LDC	Latvia	4	9	USSR/EE
Sao Tome and Principe	4	7	LLDC	Liberia	4	9	LDC
Seychelles	4	7	LDC	Panama	4	9	LDC
Tunisia	4	7	LDC	Philippines	4	9	LDC
Uruguay	4	7	LDC	Saint Kitts and Nevis	4	9	LDC

Continuation of Table VIII

Country	8 Cl.	15 Cl.	Cat.	Country	8 Cl.	15 Cl.	Cat.
Saint Lucia	4	9	LDC	Portugal	5	12	OECD
Suriname	4	9	LDC	Slovenia	5	12	USSR/EE
Tonga	4	9	LDC	Spain	5	12	OECD
Tuvalu	4	9	LLDC	Australia	6	13	OECD
Andorra	5	10		Canada	6	13	OECD
Austria	5	10	OECD	Finland	6	13	OECD
Czech Republic	5	10	*USSR/EE OECD*	Iceland	6	13	OECD
Hungary	5	10	*USSR/EE OECD*	New Zealand	6	13	OECD
Liechtenstein	5	10		Norway	6	13	OECD
Luxembourg	5	10	OECD	Sweden	6	13	OECD
San Marino	5	10		United States of America	6	13	OECD
Slovakia	5	10	*USSR/EE OECD*	Bahamas	7	14	LDC
Switzerland	5	10	OECD	Israel	7	14	
Belgium	5	11	OECD	Korea, Republic of	7	14	OECD
Denmark	5	11	OECD	Kuwait	7	14	LDC
France	5	11	OECD	Lebanon	7	14	LDC
Germany	5	11	OECD	Nauru	7	14	LDC
Italy	5	11	OECD	Netherlands Antilles	7	14	LDC
Japan	5	11	OECD	New Caledonia	7	14	LDC
Netherlands	5	11	OECD	Palau	7	14	LDC
United Kingdom	5	11	OECD	Puerto Rico	7	14	LDC
Bulgaria	5	12	USSR/EE	Qatar	7	14	LDC
Croatia	5	12	USSR/EE	United Arab Emirates	7	14	LDC
Greece	5	12	OECD	Bahrain	8	15	LDC
Ireland	5	12	OECD	Bermuda	8	15	
Lithuania	5	12	USSR/EE	Malta	8	15	

J. Table IX - Clusters from *Ward* and *K-Means*[67]

Country	8 Clusters Ward	8 Clusters K-Means	15 Clusters Ward	15 Clusters K-Means	Category
Afghanistan	1	1	1	1	LLDC
Bhutan	*2*	*1*	*2*	*1*	LLDC
Bolivia	1	1	1	1	LDC
Burkina Faso	1	1	1	1	LLDC
Burundi	1	1	1	1	LLDC
Central African Republic	1	1	1	1	LLDC
Chad	1	1	1	1	LLDC
Ethiopia	1	1	1	1	LLDC
Lao People's Dem. Rep.	1	1	1	1	LLDC
Lesotho	1	1	1	1	LLDC
Malawi	1	1	1	1	LLDC
Mali	1	1	1	1	LLDC
Mongolia	1	1	1	1	LDC
Nepal	1	1	1	1	LLDC
Niger	1	1	1	1	LLDC
Paraguay	1	1	1	1	LDC
Rwanda	1	1	1	1	LLDC
Swaziland	1	1	1	1	LDC
Uganda	1	1	1	1	LLDC
Zambia	1	1	1	1	
Zimbabwe	*2*	*1*	*2*	*1*	
Armenia	2	2	2	2	USSR/EE
Azerbaijan	2	2	2	2	USSR/EE
Belarus	2	2	2	2	USSR/EE
Botswana	2	2	2	2	LLDC

[67] The official UN category is attached again.
The data is sorted according to the results of the *K-Means* clustering with 15 clusters.
Mismatches between the two clustering algorithms are marked in italics.

Continuation of Table IX

Country	**8 Clusters Ward**	**8 Clusters K-Means**	**15 Clusters Ward**	**15 Clusters K-Means**	**Category**
Kazakhstan	2	2	2	2	USSR/EE
Kyrgyzstan	2	2	2	2	USSR/EE
Republic of Moldova	2	2	2	2	USSR/EE
Slovakia	*5*	*2*	*10*	*2*	*USSR/EE OECD*
Tajikistan	2	2	2	2	USSR/EE
The FYR of Macedonia	2	2	2	2	USSR/EE
Turkmenistan	2	2	2	2	USSR/EE
Uzbekistan	2	2	2	2	USSR/EE
Albania	3	3	3	3	USSR/EE
Bosnia and Herzegovina	3	3	3	3	USSR/EE
China a	3	3	5	3	LDC
Comoros	3	3	3	3	LLDC
Egypt	4	4	*6*	*3*	LDC
Gambia	*4*	*3*	*8*	*3*	LLDC
Haiti	3	3	3	3	LLDC
India	3	3	3	3	LDC
Indonesia	3	3	3	3	LDC
Micronesia, Fed. States of	3	3	3	3	LDC
Morocco	*4*	*3*	*6*	*3*	LDC
Nigeria	3	3	3	3	LDC
Pakistan	3	3	3	3	LDC
Sri Lanka	3	3	3	3	LDC
Thailand	3	3	3	3	LDC
Vietnam	3	3	3	3	LDC
Angola	3	3	4	4	LDC
Benin	3	3	*5*	*4*	LLDC
Cambodia	3	3	4	4	LDC
Dem. Republic of Congo***	3	3	4	4	LDC
Equatorial Guinea	3	3	*5*	*4*	LLDC
Eritrea	3	3	4	4	LLDC

Continuation of Table IX

Country	**8 Clusters Ward**	**8 Clusters K-Means**	**15 Clusters Ward**	**15 Clusters K-Means**	**Category**
Ghana	3	3	*3*	*4*	LDC
Guinea	3	3	4	4	LLDC
Guinea-Bissau	3	3	4	4	LLDC
Guyana	3	3	4	4	LDC
Kenya	3	3	4	4	LDC
Madagascar	3	3	4	4	LDC
Mozambique	3	3	4	4	LLDC
Myanmar	3	3	4	4	LLDC
Namibia	3	3	4	4	LDC
Papua New Guinea	3	3	4	4	LDC
Samoa	3	3	4	4	LLDC
Sierra Leone	3	3	4	4	LLDC
Solomon Islands	3	3	4	4	LDC
Somalia	3	3	4	4	LLDC
Sudan	3	3	*3*	*4*	LLDC
Togo	3	3	*3*	*4*	LLDC
United Rep. of Tanzania	3	3	4	4	LLDC
Vanuatu	3	3	4	4	LLDC
Yemen	3	3	4	4	LLDC
Belize	3	3	5	5	LDC
Brazil	4	4	*6*	*5*	LDC
Cameroon	3	3	5	5	LDC
Colombia	4	4	*6*	*5*	LDC
Congo, Republic***	3	3	5	5	LDC
Cte d'Ivoire	3	3	*4*	*5*	LDC
Ecuador	3	3	5	5	LDC
El Salvador	4	4	*9*	*5*	LDC
Fiji	*3*	*4*	5	5	LDC
Guatemala	3	3	5	5	LDC
Honduras	3	3	5	5	LDC

Continuation of Table IX

Country	**8 Clusters Ward**	**8 Clusters K-Means**	**15 Clusters Ward**	**15 Clusters K-Means**	**Category**
Korea, Dem. People's Rep. of	3	3	5	5	LDC
Mauritania	3	3	5	5	LLDC
Nicaragua	3	3	5	5	LDC
Peru	*3*	*4*	5	5	LDC
Philippines	*4*	*3*	*9*	*5*	LDC
Senegal	3	3	5	5	LDC
Syrian Arab Republic	3	3	5	5	LDC
Algeria	*4*	*3*	6	6	LDC
Brunei Darussalam	4	4	6	6	LDC
Cuba	4	4	*7*	*6*	LDC
French Guyana	4	4	*9*	*6*	LDC
French Polynesia	*4*	*3*	6	6	LDC
Guadeloupe	4	4	*8*	*6*	LDC
Iran (Islamic Rep. of)	4	4	6	6	LDC
Libyan Arab Jamahiriya	4	4	6	6	LDC
Malaysia	4	4	6	6	LDC
Mexico	4	4	6	6	OECD
Oman	4	4	6	6	LDC
Poland	4	4	*8*	*6*	*USSR/EE OECD*
Romania	4	4	6	6	USSR/EE
Russian Federation	4	4	6	6	USSR/EE
Saudi Arabia	4	4	6	6	LDC
South Africa	*4*	*3*	6	6	
Trinidad and Tobago	4	4	*8*	*6*	LDC
Turkey	4	4	6	6	OECD
Ukraine	4	4	6	6	USSR/EE
Venezuela	4	4	6	6	LDC

Continuation of Table IX

Country	**8 Clusters Ward**	**8 Clusters K-Means**	**15 Clusters Ward**	**15 Clusters K-Means**	**Category**
Yugoslavia	4	4	6	6	
Cape Verde	4	4	7	7	LLDC
Dominica	4	4	*9*	*7*	LDC
Georgia	4	4	7	7	USSR/EE
Iraq	4	4	7	7	LDC
Jamaica	4	4	7	7	LDC
Jordan	4	4	7	7	LDC
Sao Tome and Principe	4	4	7	7	LLDC
Seychelles	*4*	*7*	7	7	LDC
Tunisia	4	4	7	7	LDC
Uruguay	*4*	*7*	7	7	LDC
Bangladesh	*4*	*3*	8	8	LLDC
Barbados	*4*	*8*	8	8	LDC
Grenada	4	4	8	8	LDC
Mauritius	4	4	8	8	LDC
Nauru	7	7	*14*	*8*	LDC
Reunion	4	4	8	8	LDC
Saint Vincent / Grenadines	4	4	8	8	LDC
Antigua and Barbuda	4	4	9	9	LDC
Argentina	4	4	9	9	LDC
Chile	4	4	9	9	LDC
Costa Rica	*3*	*4*	*5*	*9*	LDC
Djibouti	4	4	9	9	LLDC
Dominican Republic	4	4	9	9	LDC
Estonia	4	4	9	9	USSR/EE
Gabon	4	4	9	9	LDC
Latvia	4	4	9	9	USSR/EE
Liberia	*4*	*3*	9	9	LDC
Palau	7	7	*14*	*9*	LDC
Panama	4	4	9	9	LDC

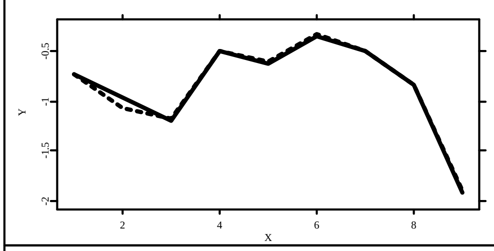
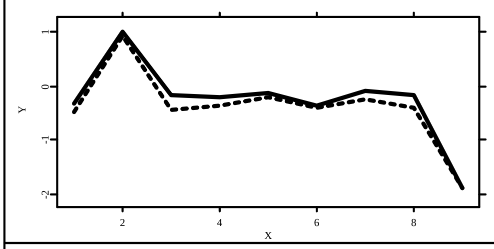
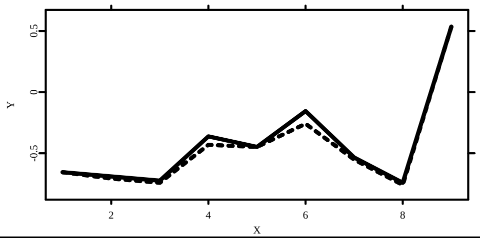
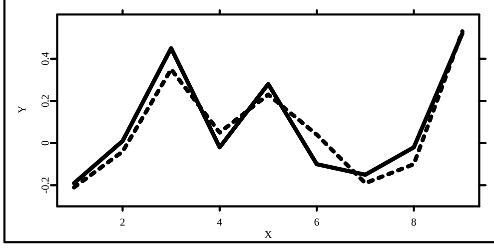
Continuation of Table IX

Country	**8 Clusters Ward**	**8 Clusters K-Means**	**15 Clusters Ward**	**15 Clusters K-Means**	**Category**
Saint Kitts and Nevis	4	4	9	9	LDC
Saint Lucia	4	4	9	9	LDC
Suriname	4	4	9	9	LDC
Tonga	*4*	*3*	9	9	LDC
Tuvalu	4	4	9	9	LLDC
Andorra	5	5	10	10	
Austria	5	5	10	10	OECD
Czech Republic	5	5	10	10	*USSR/EE OECD*
Hungary	*5*	*3*	10	10	*USSR/EE OECD*
Liechtenstein	5	5	10	10	
Luxembourg	5	5	10	10	OECD
San Marino	5	5	10	10	
Switzerland	5	5	10	10	OECD
Belgium	*5*	*8*	11	11	OECD
Denmark	5	5	11	11	OECD
France	5	5	11	11	OECD
Germany	5	5	11	11	OECD
Italy	5	5	11	11	OECD
Japan	5	5	11	11	OECD
Korea, Republic of	*7*	*5*	*14*	*11*	OECD
Netherlands	5	5	11	11	OECD
United Kingdom	5	5	11	11	OECD
Bulgaria	*5*	*4*	12	12	USSR/EE
Croatia	*5*	*4*	12	12	USSR/EE
Greece	5	5	12	12	OECD
Ireland	5	5	12	12	OECD
Lithuania	*5*	*4*	12	12	USSR/EE
New Zealand	*6*	*7*	*13*	*12*	OECD
Portugal	*5*	*7*	12	12	OECD
Puerto Rico	7	7	*14*	*12*	LDC

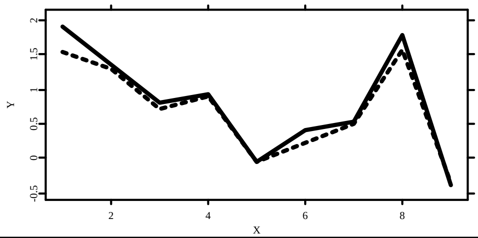
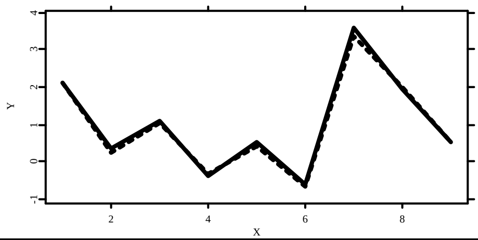
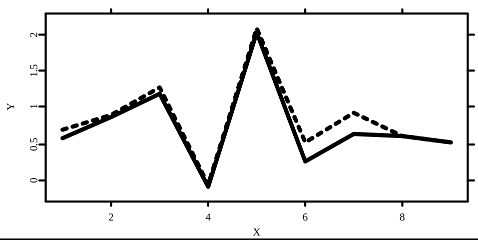
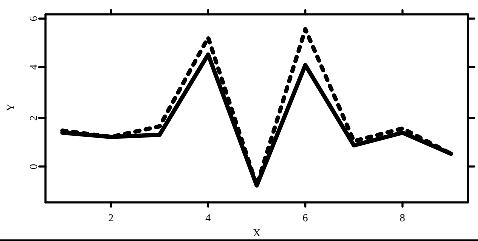
Continuation of Table IX

Country	**8 Clusters Ward**	**8 Clusters K-Means**	**15 Clusters Ward**	**15 Clusters K-Means**	**Category**
Slovenia	5	5	12	12	USSR/EE
Spain	5	5	12	12	OECD
Australia	6	6	13	13	OECD
Canada	6	6	13	13	OECD
Finland	6	6	13	13	OECD
Iceland	6	6	13	13	OECD
Norway	6	6	13	13	OECD
Sweden	6	6	13	13	OECD
United Arab Emirates	*7*	*6*	*14*	*13*	LDC
United States of America	6	6	13	13	OECD
Bahamas	7	7	14	14	LDC
Israel	7	7	14	14	
Kuwait	7	7	14	14	LDC
Lebanon	7	7	14	14	LDC
Netherlands Antilles	7	7	14	14	LDC
New Caledonia	7	7	14	14	LDC
Qatar	7	7	14	14	LDC
Bahrain	8	8	15	15	LDC
Bermuda	8	8	15	15	
Malta	8	8	15	15	

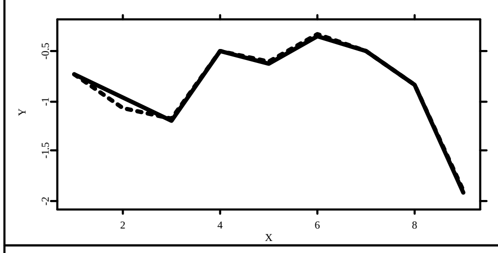
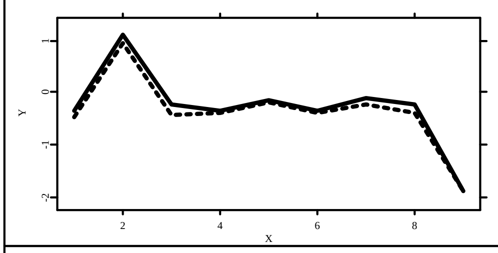
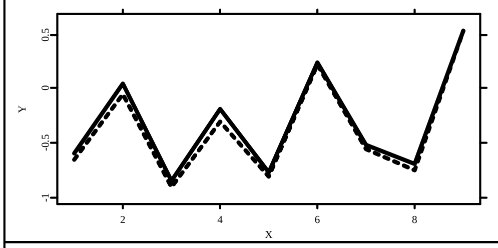
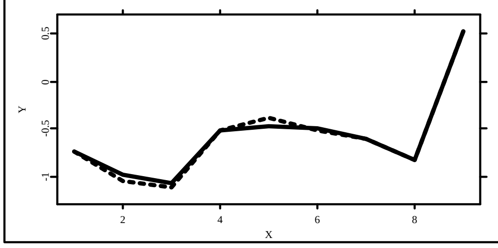
K. Comparing 8-Cluster Z-Scores for *Ward* and *K-Means*

	Clusters 1 K-Means - Solid Ward - Dashed
	Clusters 2 K-Means - Solid Ward - Dashed
	Clusters 3 K-Means - Solid Ward - Dashed
	Clusters 4 K-Means - Solid Ward - Dashed

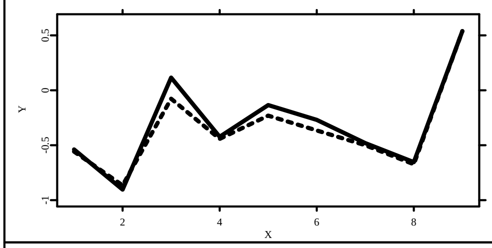
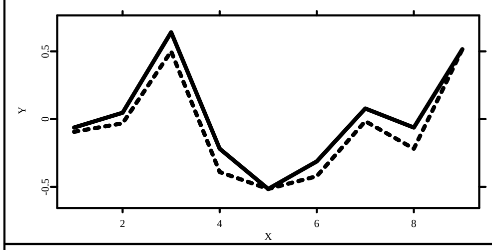
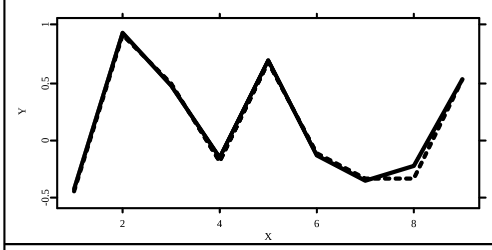
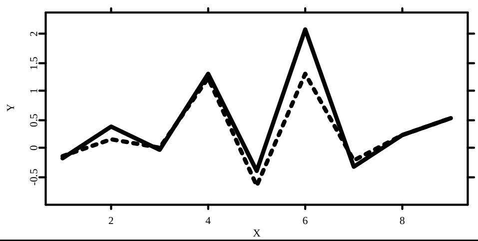
Continuation of K. Comparing 8-Cluster Z-Scores for *Ward* and *K-Means*

	Clusters 5 K-Means - Solid Ward - Dashed
	Clusters 6 K-Means - Solid Ward - Dashed
	Clusters 7 K-Means - Solid Ward - Dashed
	Clusters 8 K-Means - Solid Ward - Dashed

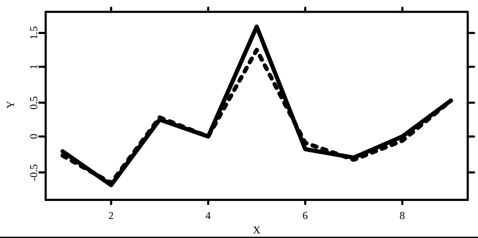
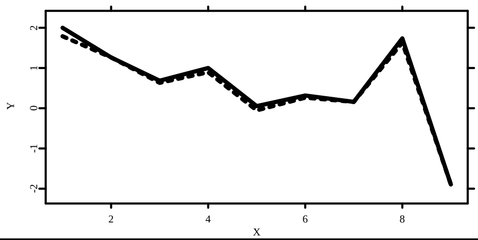
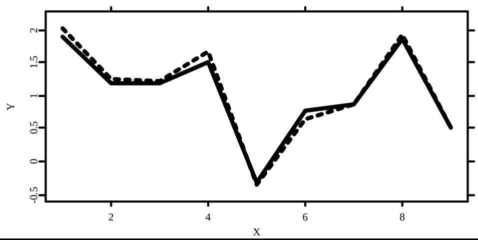
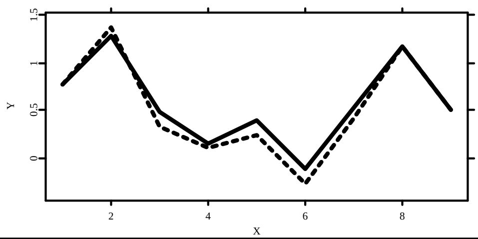
L. Comparing 15-Cluster Z-Scores for *Ward* and *K-Means*

	Clusters 1 K-Means - Solid Ward - Dashed
	Clusters 2 K-Means - Solid Ward - Dashed
	Clusters 3 K-Means - Solid Ward - Dashed
	Clusters 4 K-Means - Solid Ward - Dashed

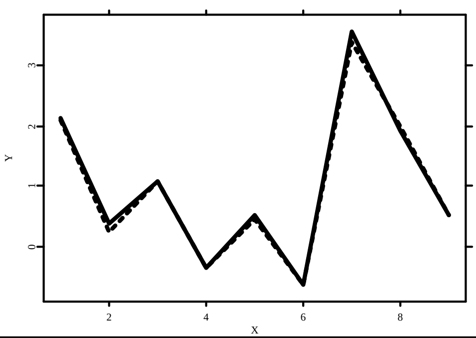
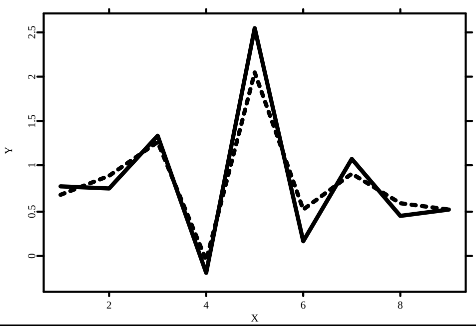
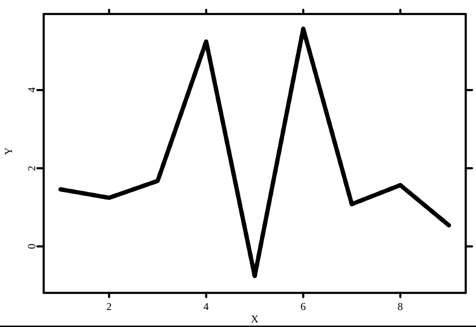
Continuation of L. Comparing 15-Cluster Z-Scores for *Ward* and *K-Means*

	Clusters 5 K-Means - Solid Ward - Dashed
	Clusters 6 K-Means - Solid Ward - Dashed
	Clusters 7 K-Means - Solid Ward - Dashed
	Clusters 8 K-Means - Solid Ward - Dashed

Continuation of L. Comparing 15-Cluster Z-Scores for *Ward* and *K-Means*

	Clusters 9 K-Means - Solid Ward - Dashed
	Clusters 10 K-Means - Solid Ward - Dashed
	Clusters 11 K-Means - Solid Ward - Dashed
	Clusters 12 K-Means - Solid Ward - Dashed

Continuation of L. Comparing 15-Cluster Z-Scores for *Ward* and *K-Means*

	Clusters 13 K-Means - Solid Ward - Dashed
	Clusters 14 K-Means - Solid Ward - Dashed
	Clusters 15 K-Means - Solid Ward - Dashed

M. Table X - Partition Matrix U obtained from 8-Clusters *Fuzzy C-Means*[68]

Country or area / Cluster	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Afghanistan	0.156	0.011	0.017	0.087	0.059	0.280	0.100	**0.291**
Albania	**0.149**	0.139	0.124	0.113	0.057	0.149	0.123	0.147
Algeria	0.080	0.134	0.175	0.032	0.138	**0.184**	0.182	0.075
Andorra	**0.287**	0.208	0.071	0.155	0.034	0.216	0.025	0.005
Angola	0.054	**0.215**	0.117	0.142	0.024	0.173	0.063	0.212
Antigua and Barbuda	**0.252**	0.081	0.223	0.015	0.086	0.082	0.208	0.053
Argentina	0.136	0.131	0.138	0.016	0.096	**0.196**	0.184	0.103
Armenia	0.039	0.132	0.185	**0.192**	0.077	0.159	0.025	0.190
Australia	0.073	0.099	0.169	0.215	0.087	0.095	**0.193**	0.069
Austria	**0.264**	0.013	0.006	0.071	0.257	0.161	0.222	0.006
Azerbaijan	**0.182**	0.180	0.114	0.155	0.049	0.100	0.072	0.149
Bahamas	0.081	0.076	**0.250**	0.147	0.007	0.131	0.124	0.183
Bahrain	0.166	**0.328**	0.015	0.199	0.040	0.149	0.029	0.074
Bangladesh	0.149	0.186	0.085	0.140	0.086	0.166	0.163	0.025
Barbados	0.053	0.014	0.134	0.161	0.125	0.152	**0.273**	0.089
Belarus	**0.207**	0.051	0.197	0.159	0.119	0.029	0.038	0.201
Belgium	0.062	0.008	0.132	0.182	0.052	0.146	0.204	**0.213**
Belize	0.031	**0.227**	0.162	0.192	0.225	0.064	0.083	0.015
Benin	**0.231**	0.063	0.243	0.075	0.231	0.089	0.009	0.058
Bermuda	0.022	0.063	0.068	0.076	0.195	0.260	**0.317**	0.001
Bhutan	0.154	0.164	**0.194**	0.180	0.131	0.152	0.015	0.010
Bolivia	0.105	0.028	0.154	0.165	**0.181**	0.149	0.093	0.125
Bosnia and Herzegovina	**0.231**	0.103	0.113	0.015	0.251	0.057	0.145	0.084

[68]Parameter values are given in the text in section 5.4.3. The largest value μ_{ij} for each observation is marked in bold.

Continuation of Table X

Country or area / Cluster	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Botswana	0.156	0.101	0.021	0.124	0.096	**0.255**	0.084	0.162
Brazil	**0.280**	0.140	0.107	0.112	0.049	0.112	0.098	0.102
Brunei Darussalam	0.100	0.005	0.184	0.211	0.078	0.209	0.189	**0.024**
Bulgaria	**0.169**	0.112	0.081	0.163	0.149	0.150	0.157	0.019
Burkina Faso	0.121	0.176	0.134	0.144	0.126	0.011	**0.213**	0.075
Burundi	0.181	0.152	0.076	0.171	0.122	**0.205**	0.040	0.053
Cambodia	0.012	0.252	0.201	0.126	0.014	0.060	**0.245**	0.091
Cameroon	0.105	0.078	0.090	0.102	**0.180**	0.121	0.177	0.147
Canada	**0.229**	0.041	0.071	0.084	0.011	0.168	0.195	0.201
Cape Verde	0.233	0.048	0.222	0.021	**0.238**	0.152	0.019	0.067
Central African Republic	0.221	0.198	0.087	0.063	0.013	0.114	0.046	**0.259**
Chad	0.009	0.068	0.053	0.058	0.074	0.194	**0.292**	0.251
Chile	0.114	**0.166**	0.153	0.123	0.154	0.093	0.080	0.117
China a	0.017	0.183	0.141	0.157	**0.228**	0.094	0.158	0.022
Colombia	**0.183**	0.088	0.132	0.166	0.181	0.015	0.119	0.117
Comoros	0.018	0.169	0.031	0.188	0.046	0.112	**0.250**	0.187
Congo, Republic***	0.107	0.113	0.117	0.014	0.119	0.213	0.101	**0.216**
Costa Rica	0.115	0.106	0.162	0.110	0.022	0.174	0.078	**0.234**
Cte d'Ivoire	0.073	**0.254**	0.077	0.073	0.140	0.231	0.131	0.021
Croatia	0.064	**0.202**	0.195	0.198	0.061	0.114	0.062	0.105
Cuba	0.132	0.063	0.163	0.130	**0.170**	0.109	0.127	0.106
Czech Republic	0.029	**0.203**	0.124	0.152	0.124	0.059	0.177	0.132
Dem. Republic of Congo***	0.030	0.144	0.152	0.100	0.077	0.008	**0.288**	0.201
Denmark	0.139	0.147	0.059	0.044	**0.224**	0.216	0.110	0.060
Djibouti	0.012	**0.285**	0.001	0.002	0.108	0.335	0.038	0.219
Dominica	0.143	0.178	0.097	0.174	**0.186**	0.027	0.052	0.143
Dominican Republic	**0.262**	0.030	0.057	0.093	0.238	0.234	0.042	0.044
Ecuador	0.124	**0.210**	0.059	0.091	0.132	0.179	0.097	0.109

Continuation of Table X

Country or area / Cluster	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Egypt	0.052	0.047	0.181	**0.318**	0.026	0.018	0.055	0.303
El Salvador	0.035	0.051	0.038	0.176	**0.226**	0.115	0.197	0.162
Equatorial Guinea	0.050	0.036	0.147	0.185	0.176	0.086	0.126	**0.193**
Eritrea	0.088	0.032	0.160	0.005	0.063	0.208	0.203	**0.242**
Estonia	0.212	**0.235**	0.122	0.077	0.068	0.210	0.019	0.056
Ethiopia	0.071	0.062	0.112	0.186	0.088	0.102	**0.226**	0.154
Fiji	0.182	**0.198**	0.012	0.166	0.078	0.165	0.171	0.027
Finland	0.090	0.160	0.128	0.110	**0.246**	0.112	0.118	0.035
France	0.132	0.195	0.019	0.003	0.217	**0.217**	0.176	0.042
French Guyana	0.156	**0.208**	0.058	0.043	0.203	0.086	0.122	0.125
French Polynesia	0.162	**0.205**	0.191	0.048	0.095	0.093	0.047	0.159
Gabon	0.150	0.079	0.166	0.022	0.164	0.125	0.055	**0.239**
Gambia	0.110	0.151	**0.211**	0.162	0.175	0.025	0.072	0.094
Georgia	0.134	0.153	0.010	**0.178**	0.153	0.129	0.120	0.123
Germany	0.134	0.082	**0.202**	0.089	0.121	0.183	0.066	0.124
Ghana	0.076	0.103	**0.369**	0.072	0.007	0.036	0.300	0.037
Greece	0.267	**0.288**	0.003	0.221	0.085	0.015	0.107	0.014
Grenada	0.156	**0.193**	0.172	0.004	0.054	0.180	0.105	0.137
Guadeloupe	0.133	0.099	0.060	0.179	0.026	**0.255**	0.086	0.162
Guatemala	0.088	0.155	0.153	**0.231**	0.003	0.051	0.170	0.151
Guinea	0.140	0.098	0.200	**0.346**	0.062	0.012	0.061	0.081
Guinea-Bissau	0.173	0.038	0.088	0.016	0.273	0.050	0.127	**0.234**
Guyana	0.063	0.198	**0.247**	0.179	0.003	0.205	0.014	0.091
Haiti	0.086	0.133	0.116	0.056	0.154	0.158	0.128	**0.169**
Honduras	0.181	0.180	0.026	0.059	0.125	0.152	**0.228**	0.049
Hungary	0.082	0.049	**0.378**	0.007	0.263	0.030	0.080	0.112
Iceland	**0.205**	0.126	0.106	0.069	0.013	0.239	0.192	0.050
India	0.124	0.134	0.058	0.098	0.143	0.034	**0.250**	0.158
Indonesia	0.146	**0.216**	0.127	0.072	0.109	0.147	0.150	0.034
Iran (Islamic Rep. of)	0.049	**0.214**	0.193	0.114	0.177	0.187	0.010	0.057

Continuation of Table X

Country or area / Cluster	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Iraq	0.081	0.037	0.171	0.188	**0.207**	0.124	0.192	0.000
Ireland	0.197	0.016	0.128	0.171	0.080	0.070	**0.229**	0.110
Israel	0.054	0.144	0.029	0.091	0.159	**0.215**	0.134	0.172
Italy	0.024	0.112	0.115	0.135	**0.276**	0.153	0.155	0.030
Jamaica	**0.195**	0.170	0.022	0.127	0.140	0.108	0.059	0.178
Japan	0.242	0.128	0.064	0.156	0.122	0.008	0.095	0.185
Jordan	0.172	0.037	0.117	0.159	0.155	**0.188**	0.030	0.142
Kazakhstan	**0.269**	0.239	0.045	0.015	0.224	0.093	0.045	0.070
Kenya	**0.220**	0.086	0.093	0.057	0.032	0.124	0.205	0.182
Korea, Dem. People's Rep. of	0.022	0.226	0.084	0.140	0.095	0.009	0.196	**0.229**
Korea, Republic of	0.092	0.041	0.150	0.014	0.065	0.175	**0.234**	0.228
Kuwait	**0.226**	0.135	0.166	0.106	0.083	0.027	0.039	0.218
Kyrgyzstan	**0.184**	0.153	0.178	0.085	0.091	0.135	0.050	0.123
Lao People's Dem. Rep.	0.065	0.051	**0.219**	0.298	0.125	0.004	0.073	0.165
Latvia	0.193	0.203	0.184	0.011	0.045	0.136	**0.217**	0.011
Lebanon	0.066	0.089	0.114	0.161	0.123	**0.176**	0.138	0.132
Lesotho	0.088	0.171	0.202	0.182	0.103	0.020	**0.224**	0.010
Liberia	0.205	0.002	0.204	0.159	0.086	**0.213**	0.086	0.046
Libyan Arab Jamahiriya	0.154	**0.238**	0.233	0.142	0.009	0.193	0.022	0.009
Liechtenstein	0.190	0.021	0.108	0.094	0.196	0.056	**0.226**	0.108
Lithuania	0.109	**0.192**	0.024	0.181	0.097	0.161	0.046	0.190
Luxembourg	**0.272**	0.184	0.096	0.139	0.039	0.091	0.007	0.172
Madagascar	0.166	**0.200**	0.146	0.116	0.089	0.185	0.069	0.030
Malawi	**0.187**	0.185	0.097	0.180	0.013	0.143	0.085	0.110
Malaysia	0.140	0.093	0.168	**0.196**	0.180	0.107	0.037	0.079
Mali	0.201	**0.269**	0.075	0.004	0.024	0.145	0.262	0.020
Malta	0.019	0.236	0.131	0.001	0.135	**0.296**	0.039	0.143
Mauritania	0.090	0.119	0.166	**0.186**	0.147	0.105	0.135	0.051

Continuation of Table X

Country or area / Cluster	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Mauritius	0.249	0.146	**0.262**	0.069	0.027	0.122	0.009	0.116
Mexico	0.201	0.132	**0.253**	0.234	0.014	0.070	0.014	0.083
Micronesia, Fed. States of	0.062	0.104	**0.220**	0.179	0.088	0.155	0.178	0.015
Mongolia	0.191	0.123	0.062	0.188	0.163	**0.211**	0.016	0.046
Morocco	0.051	0.059	**0.240**	0.178	0.150	0.042	0.157	0.122
Mozambique	0.146	**0.286**	0.151	0.045	0.053	0.103	0.072	0.144
Myanmar	0.056	**0.213**	0.187	0.140	0.136	0.060	0.129	0.079
Namibia	0.130	0.098	0.047	**0.177**	0.153	0.155	0.163	0.076
Nauru	**0.202**	0.090	0.102	0.079	0.073	0.124	0.162	0.168
Nepal	0.145	0.129	0.103	0.036	0.096	0.113	0.121	**0.256**
Netherlands	0.168	0.022	0.026	0.181	**0.214**	0.016	0.178	0.195
Netherlands Antilles	0.136	**0.221**	0.029	0.116	0.004	0.197	0.148	0.149
New Caledonia	0.106	0.202	0.042	0.066	**0.202**	0.079	0.116	0.186
New Zealand	**0.257**	0.195	0.047	0.134	0.199	0.029	0.031	0.109
Nicaragua	0.038	0.191	0.173	0.165	0.118	0.086	**0.204**	0.024
Niger	0.107	0.111	0.168	0.032	0.191	**0.198**	0.127	0.066
Nigeria	0.180	0.062	0.045	0.064	0.103	0.069	**0.266**	0.212
Norway	**0.220**	0.108	0.208	0.099	0.151	0.060	0.124	0.029
Oman	0.019	0.211	0.127	0.017	0.209	**0.216**	0.047	0.154
Pakistan	0.109	0.161	0.011	0.209	0.126	0.085	0.063	**0.237**
Palau	**0.220**	0.143	0.208	0.151	0.083	0.156	0.006	0.033
Panama	0.169	0.021	**0.198**	0.162	0.071	0.081	0.190	0.107
Papua New Guinea	0.102	0.067	0.060	0.205	0.126	0.042	**0.228**	0.171
Paraguay	0.179	0.009	0.161	0.144	**0.207**	0.132	0.039	0.130
Peru	0.094	**0.178**	0.130	0.159	0.168	0.147	0.016	0.108
Philippines	0.110	0.103	0.064	0.180	0.065	0.060	0.150	**0.267**
Poland	**0.208**	0.043	0.066	0.141	0.123	0.180	0.174	0.066
Portugal	0.158	0.188	0.043	0.026	0.107	0.003	**0.242**	0.233
Puerto Rico	0.164	0.083	0.082	**0.164**	0.152	0.096	0.117	0.141
Qatar	0.060	0.033	0.161	0.175	**0.207**	0.127	0.134	0.103

Continuation of Table X

Country or area / Cluster	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Republic of Moldova	0.139	0.091	0.148	0.013	0.079	0.192	**0.197**	0.140
Reunion	0.004	0.242	**0.304**	0.021	0.048	0.009	0.107	0.265
Romania	0.133	0.183	0.021	0.018	0.167	0.080	0.187	**0.211**
Russian Federation	0.077	**0.250**	0.078	0.042	0.135	0.202	0.034	0.182
Rwanda	0.082	0.153	0.106	0.140	0.110	0.125	0.044	**0.241**
Saint Kitts and Nevis	0.183	0.008	0.139	0.020	0.080	0.206	**0.209**	0.154
Saint Lucia	0.124	0.154	**0.178**	0.033	0.118	0.090	0.131	0.172
Saint Vincent / Grenadines	0.123	0.069	0.135	0.137	0.092	**0.199**	0.157	0.088
Samoa	0.162	0.005	0.029	0.002	0.177	**0.357**	0.174	0.093
San Marino	0.053	0.252	0.010	0.004	**0.290**	0.225	0.031	0.136
Sao Tome and Principe	0.125	0.072	0.100	0.055	**0.214**	0.101	0.204	0.130
Saudi Arabia	0.046	**0.194**	0.121	0.111	0.158	0.193	0.042	0.136
Senegal	0.190	0.089	**0.197**	0.066	0.013	0.138	0.122	0.186
Seychelles	0.142	0.025	0.111	0.104	0.149	**0.202**	0.126	0.141
Sierra Leone	0.146	0.109	0.146	0.078	**0.175**	0.107	0.114	0.124
Slovakia	0.041	**0.305**	0.032	0.167	0.157	0.098	0.098	0.102
Slovenia	**0.205**	0.120	0.086	0.078	0.000	0.199	0.187	0.126
Solomon Islands	0.057	0.209	0.179	0.079	0.002	0.072	**0.299**	0.104
Somalia	0.048	0.220	0.010	0.177	0.108	0.162	0.060	**0.215**
South Africa	0.287	0.097	0.253	0.087	0.124	0.012	0.013	0.127
Spain	0.110	0.136	0.103	0.066	**0.214**	0.127	0.185	0.060
Sri Lanka	0.025	0.072	0.006	0.161	**0.245**	0.208	0.097	0.187
Sudan	0.086	0.109	0.106	**0.191**	0.168	0.190	0.051	0.099
Suriname	**0.210**	0.140	0.069	0.171	0.149	0.018	0.101	0.143
Swaziland	0.234	0.013	0.081	0.011	0.155	**0.279**	0.036	0.191
Sweden	0.119	0.011	0.159	0.204	**0.205**	0.045	0.140	0.117
Switzerland	0.087	0.054	0.183	0.003	0.199	0.054	0.128	**0.292**
Syrian Arab Republic	0.007	0.034	0.199	0.141	0.188	**0.240**	0.070	0.123

Continuation of Table X

Country or area / Cluster	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Tajikistan	0.035	0.176	0.029	**0.249**	0.094	0.235	0.052	0.130
Thailand	0.097	0.009	0.200	0.198	0.117	0.062	0.076	**0.241**
The FYR of Macedonia	**0.216**	0.095	0.117	0.013	0.084	0.163	0.196	0.115
Togo	0.199	0.084	0.083	0.026	0.068	0.095	0.199	**0.246**
Tonga	0.038	0.127	0.041	**0.209**	0.141	0.116	0.174	0.153
Trinidad and Tobago	0.002	0.140	0.211	0.089	**0.264**	0.016	0.182	0.096
Tunisia	**0.233**	0.139	0.100	0.172	0.154	0.157	0.025	0.019
Turkey	0.178	0.170	0.191	0.077	0.070	0.080	**0.198**	0.037
Turkmenistan	**0.173**	0.103	0.124	0.092	0.057	0.100	0.246	0.104
Tuvalu	0.005	0.094	**0.207**	0.178	0.091	0.156	0.105	0.163
Uganda	**0.239**	0.128	0.081	0.160	0.027	0.073	0.214	0.078
Ukraine	**0.232**	0.137	0.015	0.156	0.083	0.196	0.072	0.110
United Arab Emirates	0.088	**0.281**	0.026	0.235	0.203	0.016	0.112	0.037
United Kingdom	**0.255**	0.153	0.072	0.145	0.140	0.018	0.125	0.092
United Rep. of Tanzania	0.005	0.153	0.133	0.095	0.154	**0.217**	0.100	0.144
United States of America	0.036	**0.164**	0.213	0.119	0.170	0.044	0.105	0.148
Uruguay	0.127	0.102	0.107	0.044	0.166	0.144	**0.251**	0.059
Uzbekistan	0.076	0.011	0.165	0.148	0.162	0.042	**0.227**	0.169
Vanuatu	0.175	0.140	0.027	0.047	**0.177**	0.154	0.100	0.181
Venezuela	0.216	**0.244**	0.059	0.023	0.117	0.077	0.175	0.088
Vietnam	**0.212**	0.006	0.117	0.173	0.185	0.075	0.048	0.183
Yemen	0.102	0.067	0.133	0.114	**0.230**	0.182	0.166	0.006
Yugoslavia	**0.204**	0.169	0.006	0.051	0.247	0.184	0.124	0.014
Zambia	0.004	0.037	0.119	0.208	0.174	0.079	**0.242**	0.137
Zimbabwe	0.022	0.247	0.128	0.208	0.005	**0.246**	0.110	0.034

N. Table XI - Clusters obtained from *Ward* Clustering omitting variable *Landlocked*

Country	Cluster	Category	Country	Cluster	Category
Afghanistan	1	LLDC	French Polynesia	1	LDC
Albania	1	USSR/EE	Ghana	1	LDC
Angola	1	LDC	Guatemala	1	LDC
Belize	1	LDC	Guinea	1	LLDC
Benin	1	LLDC	Guinea-Bissau	1	LLDC
Bhutan	1	LLDC	Guyana	1	LDC
Bosnia and Herzegovina	1	USSR/EE	Haiti	1	LLDC
Burkina Faso	1	LLDC	Honduras	1	LDC
Burundi	1	LLDC	Indonesia	1	LDC
Cambodia	1	LDC	Kenya	1	LDC
Cameroon	1	LDC	Korea, Dem. People's Rep. of	1	LDC
Central African Republic	1	LLDC	Lao People's Dem. Rep.	1	LLDC
Chad	1	LLDC	Lesotho	1	LLDC
China a	1	LDC	Madagascar	1	LDC
Cte d'Ivoire	1	LDC	Malawi	1	LLDC
Dem. Republic of Congo	1	LDC	Mali	1	LLDC
Ecuador	1	LDC	Mauritania	1	LLDC
Equatorial Guinea	1	LLDC	Micronesia, Fed. States of	1	LDC
Eritrea	1	LLDC	Mozambique	1	LLDC
Ethiopia	1	LLDC	Myanmar	1	LLDC

Continuation of Table XI

Country	**Cluster**	**Category**	**Country**	**Cluster**	**Category**
Namibia	1	LDC	Zimbabwe	1	
Nepal	1	LLDC	Algeria	2	LDC
Niger	1	LLDC	Azerbaijan	2	USSR/EE
Nigeria	1	LDC	Belarus	2	USSR/EE
Pakistan	1	LDC	Botswana	2	LLDC
Papua New Guinea	1	LDC	Bulgaria	2	USSR/EE
Rwanda	1	LLDC	Cape Verde	2	LLDC
Samoa	1	LLDC	Comoros	2	LLDC
Senegal	1	LDC	Croatia	2	USSR/EE
Sierra Leone	1	LLDC	Czech Republic	2	*USSR/EE OECD*
Solomon Islands	1	LDC	Egypt	2	LDC
Somalia	1	LLDC	Fiji	2	LDC
Sudan	1	LLDC	Georgia	2	USSR/EE
Swaziland	1	LDC	Iran (Islamic Rep. of)	2	LDC
Syrian Arab Republic	1	LDC	Iraq	2	LDC
Togo	1	LLDC	Jordan	2	LDC
Tonga	1	LDC	Kazakhstan	2	USSR/EE
Uganda	1	LLDC	Kyrgyzstan	2	USSR/EE
United Rep. of Tanzania	1	LLDC	Lithuania	2	USSR/EE
Vanuatu	1	LLDC	Malaysia	2	LDC
Vietnam	1	LDC	Morocco	2	LDC
Yemen	1	LLDC	Poland	2	*USSR/EE OECD*
Zambia	1		Republic of Moldova	2	USSR/EE

Continuation of Table XI

Country	Cluster	Category	Country	Cluster	Category
Romania	2	USSR/EE	Netherlands Antilles	3	LDC
Russian Federation	2	USSR/EE	New Caledonia	3	LDC
Sao Tome and Principe	2	LLDC	Palau	3	LDC
Slovakia	2	USSR/EE OECD	Portugal	3	OECD
Slovenia	2	USSR/EE	Puerto Rico	3	LDC
Sri Lanka	2	LDC	Qatar	3	LDC
Tajikistan	2	USSR/EE	Saint Kitts and Nevis	3	LDC
Thailand	2	LDC	Seychelles	3	LDC
The FYR of Macedonia	2	USSR/EE	Uruguay	3	LDC
Tunisia	2	LDC	Argentina	4	LDC
Turkmenistan	2	USSR/EE	Bolivia	4	LDC
Ukraine	2	USSR/EE	Brazil	4	LDC
Uzbekistan	2	USSR/EE	Brunei Darussalam	4	LDC
Yugoslavia	2		Chile	4	LDC
Andorra	3		Colombia	4	LDC
Antigua and Barbuda	3	LDC	Congo, Republic	4	LDC
Armenia	3	USSR/EE	Costa Rica	4	LDC
Bahamas	3	LDC	Cuba	4	LDC
Greece	3	OECD	Djibouti	4	LLDC
Israel	3		Dominica	4	LDC
Kuwait	3	LDC	Dominican Republic	4	LDC
Lebanon	3	LDC	El Salvador	4	LDC
Nauru	3	LDC	Estonia	4	USSR/EE

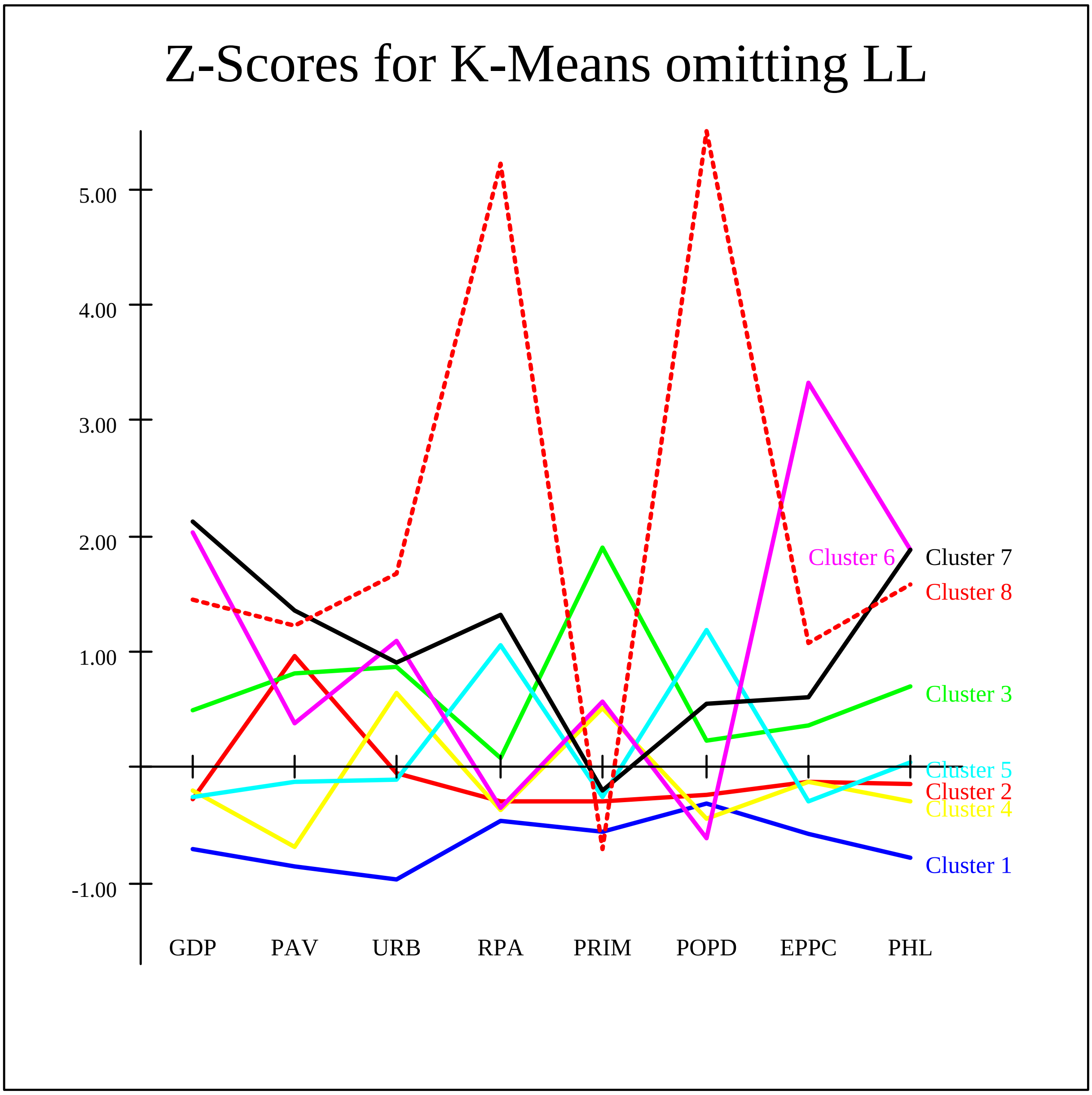
Continuation of Table XI

Country	**Cluster**	**Category**	**Country**	**Cluster**	**Category**
French Guyana	4	LDC	India	5	LDC
Gabon	4	LDC	Jamaica	5	LDC
Latvia	4	USSR/EE	Mauritius	5	LDC
Liberia	4	LDC	Philippines	5	LDC
Libyan Arab Jamahiriya	4	LDC	Reunion	5	LDC
Mexico	4	OECD	Saint Lucia	5	LDC
Mongolia	4	LDC	Saint Vincent / Grenadines	5	LDC
Nicaragua	4	LDC	Trinidad and Tobago	5	LDC
Oman	4	LDC	Tuvalu	5	LLDC
Panama	4	LDC	Australia	6	OECD
Paraguay	4	LDC	Canada	6	OECD
Peru	4	LDC	Finland	6	OECD
Saudi Arabia	4	LDC	Iceland	6	OECD
South Africa	4		New Zealand	6	OECD
Suriname	4	LDC	Norway	6	OECD
Turkey	4	OECD	Sweden	6	OECD
Venezuela	4	LDC	United Arab Emirates	6	LDC
Bangladesh	5	LLDC	United States of America	6	OECD
Barbados	5	LDC	Austria	7	OECD
Gambia	5	LLDC	Belgium	7	OECD
Grenada	5	LDC	Denmark	7	OECD
Guadeloupe	5	LDC	France	7	OECD
Hungary	5	*USSR/EE OECD*	Germany	7	OECD

Continuation of Table XI

Country	**Cluster**	**Category**
Ireland	7	OECD
Italy	7	OECD
Japan	7	OECD
Korea, Republic of	7	OECD
Liechtenstein	7	
Luxembourg	7	OECD
Netherlands	7	OECD
San Marino	7	
Spain	7	OECD
Switzerland	7	OECD
United Kingdom	7	OECD
Bahrain	8	LDC
Bermuda	8	
Malta	8	

O. Z-Scores for 8 Cluster Using *K-Means* Method and Omitting variable *Landlocked*



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Erklärung zur Urheberschaft

Hiermit erkläre ich, dass ich die vorliegende Arbeit allein und nur unter Verwendung der aufgeführten Hilfsmittel angefertigt habe.

Henning A. Speck

Berlin, den 10. März 2003