An Empirical Analysis of Growth Regimes*

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April 8, 2010

Abstract

In this paper we apply cluster analysis to a dataset on economic growth in 61 countries for the period 1960-1985. We find four clusters of countries and show that they correspond to four growth regimes (stages of growth), and highlight which factors characterize the membership of a country to a growth regime. In particular: human capital and institutional quality appear increasing in the stages of growth, while other factors such as Government consumption, investment in physical capital, trade openness and natural resource abundance show a nonmonotonic pattern across growth regimes. Finally, we show that convergence emerges as a strong force only at the highest levels of development.

1 Introduction

The empirical analysis of economic growth has attracted increasing interest over the last decades. After years of intense research, however, agreement seems far from being reached on two related issues: i) the shape of the growth path, i. e. the dynamic relation between the growth rate and income/productivity levels and, ii) the determinants of economic growth, i. e. the factors that contribute, positively or negatively, to the growth of income or productivity (Durlauf *et al.* (2005)).

The shape of the growth path is related to the issue of convergence, i. e. to the tendency for economies with different initial levels of income or productivity to reach in the long run similar income/productivity levels. Different theories provide different predictions on the shape of the growth path and therefore on convergence. The competing theories are: i) the neoclassical model of Solow (1956), predicting conditional convergence, ii) the endogenous growth models

*Thanks to seminar participants in Naples (conference on "Poverty Traps: an Empirical and Theoretical Assessment") and Palermo, and to Carlo Altavilla, Michele Battisti and Kurt Hornik for useful suggestions. Usual disclaimer applies.

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of Romer (1986), Lucas (1988) and others, predicting divergence, and iii) the nonlinear growth models, in which the growth process is characterized by different stages, or *growth regimes*.[1] These models may feature multiple equilibria and poverty traps (e. g. Azariadis and Drazen (1990)), or transitions to economic development through stages of growth (e. g. Rostow (1959) and Galor (2005)). If multiple equilibria exist, then the convergence process is defined *club convergence*.[2]

Studies on the determinants of economic growth, instead, allowed to identify a long list of explanatory variables (the Appendix B in Durlauf *et al.* (2005) contains 145 items). This contributed to shed light on the issue, but also introduced other problems such as *parameter heterogeneity*, i. e. the existence of different marginal effects of growth determinants in different economies (see, e. g. Durlauf *et al.* (2001)), and *model uncertainty*, i. e. the difficulty of selecting the relevant variables to be included in growth regressions (see, e. g., Fernàndez *et al.* (2001) and Sala-i-Martin *et al.* (2004)).[3]

Growth determinants have a specific connection with the growth path and convergence in the studies of growth regimes. In particular, some studies utilize the initial levels of some variables (e. g. productivity, human capital) to classify countries into regimes, on the assumption that a specific neoclassical production function then characterizes the regime (Durlauf and Johnson (1995), Durlauf *et al.* (2001), Papageorgiou and Masanjala (2004)). Other studies (Desdoigts (1999), Tan (2009)), instead, utilize a larger set of variables to partition a sample of countries, and separately study the growth behavior *within* the identified clusters, without specific assumptions on production functions.

In this paper we aim at contributing to this relatively small body of studies. Our starting point is a re-examination of the results in Desdoigts (1999), when variables not utilized in that study, e. g. institutions, trade and natural resources, are taken into account and a general clustering technique, based on correlations among objects, is used. In particular, we apply the clustering algorithm of Giada and Marsili (2001) and Giada and Marsili (2002) (GM henceforth) to a dataset on economic growth. As in previous studies, we partition a sample of countries on the basis of a set of variables (*features*) but, differently from previous studies, we also partition the features within each cluster of countries, in order to gain insights on the characteristics of the growth model within subsets of countries.[4]

We find that countries in our sample can be partitioned in four clusters, and show that these groups are consistent with four growth regimes, as those identified by Fiaschi and Lavezzi

[1]In this paper, with a slight abuse of terminology, we will use *growth regimes* and *stages of growth* interchangeably.

[2] Galor (1996) and Durlauf *et al.* (2005), pp. 582-604, provide recent accounts of this debate, and of the existing empirical support for the alternative theories.

[3] Durlauf *et al.* (2005), pp. 608-616, provide summaries on these topics.

[4]This exercise in similar in spirit to Masanjala and Papageorgiou (2009), who search for different growth models that can apply to Sub-Saharan and Non Sub-Saharan countries, using Bayesian Model Averaging (BMA).

(2003). The first group of countries includes Sub-Saharan countries, the second and the third contain Latin American, Asian, and African countries, while the fourth group includes OECD countries. The sequence of growth regimes is consistent with the existence of a nonlinear growth path and multiple equilibria. That is, the four regimes are characterized first of all by a different relationship between the growth rate and the level of productivity: in the first regime the growth rate is low and volatile, and a poverty trap at low productivity levels is likely to exist; in the second regime productivity is higher, and growth is positive or negative, consistent with the presence of an unstable equilibrium; in the third regime growth becomes sustained, while in the fourth regime growth is positive and a clear tendency for convergence at high productivity levels emerges.

Moreover, when we analyze the role of countries' features in characterizing clusters' membership, and therefore possible transitions across growth regimes, we find that: human capital and institutional quality are increasing in the stages of growth; other variables such as Government consumption, investments in physical capital, trade openness and natural resources, instead, display a nonmonotonic pattern across growth regimes.[5]

Finally, when we apply the clustering algorithm to the features within each cluster of countries, we find that growth regimes are also different in terms of the strength of the features' correlations. In particular, a strong negative correlation between the growth rate and initial productivity, indicating convergence, emerges at the highest development stage only.

Our results, therefore, provide support to theories of economic growth as a nonlinear process taking place through different stages of growth, and allow to reject the hypothesis of conditional convergence.[6] In addition, we argue that different countries' features (initial values or not, as in Desdoigts (1999)), can have different importance at different stages of development. The stages that we identify, however, differ from those of, e. g., Durlauf and Johnson (1995) and Papageorgiou and Masanjala (2004), in that we do not assume that the growth model within each regime is neoclassical but, on the contrary, allow the characteristics of the growth model to endogenously emerge.

In the light of these results, we also propose a reconsideration of previous findings. In particular, we show that some of Desdoigts (1999)'s results actually receive partial support by the data, in particular those on the role of religion and on convergence; that the positive effect of equipment investment (e. g. De Long and Summers (1991)) and trade openness (e. g. Frankel and Romer (1999)), or the negative effect of natural resources abundance on growth (e. g. Sachs and Warner (1995a)), may exist at certain stages of development only and, finally, that the lack of convergence found by Durlauf and Johnson (1995) and Papageorgiou and Masanjala (2004) for the group of developed countries is dubious.[7]

[5] We remark from the outset that the emphasis in this paper is on correlations, as our method does not allow to explicitly tackle the issue of causality. See also the remarks in Tan (2009), p. 11.

[6] See, e. g. Barro and Sala-i-Martin (2004).

[7] Our results on convergence among OECD countries is, on the contrary, consistent with Dowrick and Nguyen

The rest of the paper is organized as follows. Section 2 presents the methodology for the empirical analysis; Section 3 describes our dataset; Section 4 contains the results; Section 5 provides further discussion; Section 6 concludes. Appendices contain information on data and several robustness tests.

2 Methodology

Consider a set of N objects each of which is defined in terms of D measurable features, so that each object is represented by a vector $\vec{\xi}_i \in R^D$, $i = 1, \ldots, N$. We assume for simplicity that data are normalized: $\vec{\xi}_i \cdot \vec{e} = 0$ where $\vec{e} = (1, 1, \ldots, 1)$ and $\|\xi_i\|^2 = \vec{\xi}_i \vec{\xi}_i = 1$. In our case, the objects may be N countries, each characterized by D factors (see later). But objects may also be N economic factors and features be the values these attain in a group of D countries.

The problem of classifying these N objects into different classes goes under the name of data clustering. Naively one would like to have similar objects classified in the same cluster, but in practice one faces a number of problems: What does it mean similar? What is the "right" number of clusters? Which principle to follow? All these questions do not have an unique answer. That's why data Clustering has been regarded as an *ill defined* problem.

We resort to a recent data clustering technique (Giada and Marsili (2001), Giada and Marsili (2002)) that circumvents these difficulties by using the maximum likelihood principle and a simple statistical hypothesis: *similar objects have something in common*. In mathematical terms, we let s_i be the label of the cluster to which object i belongs, and $A_s = \{i : \; s_i = s\}$ be the set of objects with $s_i = s$. We assume that:

$$\vec{\xi}_i = g_{s_i} \vec{\eta}_{s_i} + \sqrt{1 - g_{s_i}^2}\, \vec{\epsilon}_i. \tag{1}$$

Here $\vec{\eta}_s$ denotes the *common* component shared by all objects $i \in A_s$ and $g_s \in [-1, 1]$ weights the common component against the individual one $\vec{\epsilon}_i$. Eq. (1) is a statistical hypothesis where g_s and s_i are the parameters to be fitted.

We first assume that both $\vec{\eta}_s$ and $\vec{\epsilon}_i$ are Gaussian vectors in R^D, with zero average and unit variance ($E[\|\eta_s\|^2] = E[\|\epsilon_i\|^2] = 1$). Later we shall come back to this assumption. Giada and Marsili (2001) show that, under the Gaussian hypothesis, it is possible to compute the likelihood of the parameters $\mathcal{G} = \{g_s\}$ and $\mathcal{S} = \{s_i\}$. The likelihood is maximal when:

$$g_s = \sqrt{\max\left[0, \frac{c_s - n_s}{n_s^2 - n_s}\right]} \tag{2}$$

where $n_s = |A_s|$ is the number of objects in cluster s and:

$$c_s = \sum_{i,j \in A_s} \vec{\xi}_i \vec{\xi}_j.$$

(1989).

is the sum of the (empirical) correlation coefficients $\vec{\xi}_i\vec{\xi}_j$ of objects in the s^{th} cluster.

The maximum log-likelihood per feature takes the form:

$$\mathcal{L}_c(\mathcal{S}) = \frac{1}{2} \sum_{s:\ n_s>1} \left[\log \frac{n_s}{c_s} + (n_s - 1) \log \frac{n_s^2 - n_s}{n_s^2 - c_s}\right].$$

Note that a cluster with a single isolated object ($n_s = c_s = 1$), or a cluster of uncorrelated objects ($c_s = n_s$) gives a vanishing contribution to the log-likelihood. The log-likelihood gives a measure of the statistical significance of a cluster structure.[8] The difference $\Delta_{\mathcal{L}_c} = \mathcal{L}_c(\mathcal{S}) - \mathcal{L}_c(\mathcal{S}/\{i\})$ of the log-likelihood of a structure $\mathcal{S}$ and the log-likelihood of the same structure without object i gives us a measure of the significance with which object i belongs to the cluster s_i. This difference, called *significance* for short, will be reported in the tables below.

If the data-set is not Gaussian, the log-likelihood takes a different form which may be much more complex than $\mathcal{L}_c(\mathcal{S})$ above. However, unless the data set is extremely rich, it may be hard to obtain a statistically significant estimate of both the distribution and of the cluster structure from it. The parsimonious description of Gaussian data-sets can be extended to more general cases by using non-parametric correlations.[9] In few words our approach relies on the assumption that deviation from normality are not relevant. Appendix B addresses this issue, showing that departures from normality, though present, do not significantly affect the results (a point which is further reinforced in Appendix C.2 by comparing our results with those obtainable with other clustering techniques).

This contrasts with the approach followed by Desdoigts (1999), the exploratory projection pursuit (EPP), by which multidimensional objects are projected in a two-dimensional space. In this approach normality is considered as an index of uninterestingness, as normality (in the projection or in the data) is synonymous of absence of structure. Moreover, cluster identification in Desdoigts (1999) is done by visual inspection, or by identifying threshold distances between points on a 2 dimensional projection space.

Several algorithms for finding an approximate maximum of $\mathcal{L}_c$ over the space of cluster structures $\mathcal{S}$ have been discussed in Giada and Marsili (2002). We used simulated annealing, which yields more accurate results (the codes are available on the internet, see Giada and Marsili (2002)).

[8] Cluster structures in uncorrelated samples of points usually result in small clusters with values of the log-likelihood of around $10^{-2} \div 10^{-3}$ (two/three orders of magnitude smaller than the clusters we discuss below).

[9] The procedure is the following: 1) compute the non-parametric correlation matrix of Kendall's τ coefficients of the original data-set 2) consider an equivalent Gaussian data-set with the same non parametric correlation matrix 3) perform data clustering on the equivalent Gaussian data-set. See Giada and Marsili (2001) for details. A check of the extent to which deviation from Gaussian behavior is relevant can be assessed comparing the cluster structure obtained in this way with that obtained disregarding deviation from normality altogether.

3 Data

Our database contains data on 61 countries for the period 1960-1985.[10] It includes the ten variables utilized by Desdoigts (1999), originally used by De Long and Summers (1991), and three variables that have recently received considerable attention by growth researchers: the quality of institutions, trade openness, and natural resource abundance.[11]

For each country, therefore, we have thirteen *features*: the average productivity growth rate over the period (G6085), the average labor force growth (LF6085), the initial productivity level, expressed as a gap with respect to the United States (GGap60), the level of primary (PE60) and secondary school (SE60) enrollment in 1960, the average share of government consumption on GDP (GovC),[12] four components of equipment investment, expressed as shares with respect to GDP: transport (Transp), structures (Struct), electrical machinery (ElMach) and nonelectrical machinery (NoElMa), a measure of institutional quality (FreeS), a measure of trade openness (Trade), and a measure of natural resource abundance (MinDep).

Given that in the literature there are no unambiguous measures of institutional quality and natural resource abundance, we consider some alternative definitions for both, while we account for the degree of trade openness by the standard measure of import plus exports on GDP.[13] In particular, we use as our main variable for institutional quality a composite index of the level of political rights and civil liberties, based on Freedom House (2007),[14] which captures the degree of democracy prevailing in a state. Other works on institutions and growth used variables from the *International Country Risk Guide*, intended to capture risks of expropriation (e.g. Knack and Keefer (1995) and Hall and Jones (1999)),[15] or other measures of government effectiveness (see Kaufmann *et al.* (2006)). However, the period covered in our sample prevents us from using these data. Following the remarks of Glaeser *et al.* (2004), we use as alternative measures of institutional quality two measures of constraints on governments from Marshall and Jaggers (2005) (xConstIn and xConstAv).[16]

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[10] Appendix A.2 contains the country list.

[11] See, among others, Glaeser *et al.* (2004) and Acemoglu *et al.* (2005) on institutions, Frankel and Romer (1999) and Alcalà and Ciccone (2004) on trade openness, Sachs and Warner (1995a), and Boschini *et al.* (2007) on natural resources. Table 14 in Appendix A.1 contains the details on the variables.

[12] This variable is intended to capture government's: "outlays that do not enhance productivity" (Barro (1996), p. 7).

[13] But see Sachs and Warner (1995b) for a richer analysis of the measurement of trade openness.

[14] The definitions of political rights and civil liberties, from `http://www.freedomhouse.org`, are: "Political rights enable people to participate freely in the political process, including the right to vote freely for distinct alternatives in legitimate elections, compete for public office, join political parties and organizations, and elect representatives who have a decisive impact on public policies and are accountable to the electorate. Civil liberties allow for the freedoms of expression and belief, associational and organizational rights, rule of law, and personal autonomy without interference from the state".

[15] Interestingly, Hall and Jones (1999) consider the average of institutional quality and trade openness as a measure of "social infrastructure".

[16] Glaeser *et al.* (2004) criticize the use of the variables from the *International Country Risk Guide* and

Finally, to account for natural resource abundance we use a measure from World Bank (2006), based on the share from extracted metals on national income (MinDep) and, alternatively, another measure from World Bank (2006) which accounts for the weight of minerals in exports (Ores).[17] These measures focus on minerals and metals and, therefore, are narrower than, e. g., the measures of natural resources originally utilized in Sachs and Warner (1995a), which also included meat, fish and dairy products. Indeed, the recent paper by Boschini *et al.* (2007) suggests that the "resource curse", i. e. a negative effect of natural resources on economic growth, may actually hold for the most *appropriable* natural resources such as minerals and precious metals and, in addition, that it strongly depends on institutional quality.[18]

In line with the remarks of Desdoigts (1999), p. 310, we notice that the features refer to various aspects of the growth process: initial conditions (Ggap60, PE60 and SE60), conditions that reflect the environment where the economic activity takes place (FreeS, Trade, MinDep), as well as conditions regarding the accumulation process over the period (Transp, Struct, ElMach, NoElMa, GovC). These features may also be classified as "proximate" (PE60, SE60, Transp, Struct, ElMach, NoElMa, GovC, Trade) and "ultimate (FreeS, MinDep) factors affecting growth" (see, e. g., Weil (2005), p. 33), where the latter factors refer to "fundamental", i.e. deeper, factors that should in principle determine the "proximate" factors. Overall, we submit that our choice of variables is parsimonious but, as we will show, nonetheless able to capture salient aspects of the growth process.[19] In addition, we do not specify any ex-ante relation between these sets of variables, in particular on possible specific correlations between proximate and fundamental variables, and allow these correlations to endogenously emerge.

Figure 1 contains a scatter plot of the average growth rate against the initial productivity level, expressed by the gap with respect to US productivity.

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from Kaufmann *et al.* (2006) arguing that they do not actually measure constraints on government and are quite volatile. In other words, these variables are not well-suited to test the causal impact of institutions on growth. The measure on constraints on governments from Marshall and Jaggers (2005) does not completely escape this criticism. However, we use it as it is available for the period of interest and, in addition, as in this paper the issue of causality is not crucial.

[17]For the exact definitions of these variables, see Table 14.

[18] Atkinson and Hamilton (2003) use the same variable utilized in this paper as a measure of resource abundance and as a component of the "genuine saving rate" of a country. The latter is a composite measure of savings that takes into account: "the extent to which countries are, on balance, liquidating or creating national wealth" (Atkinson and Hamilton (2003), p. 1801).

[19]Clearly, the list of potentially relevant variables might be different. However, the number of variables that recent works have identified as "important" in the empirical analysis of economic growth, is quite small. For example, Sala-i-Martin *et al.* (2004) using BMA find that only 18 out of 67 variables are significantly related to growth. Using a similar methodology, Fernàndez *et al.* (2001), p. 569, find that: "the 76 models with posterior probabilities over 0.1% all have in between 6 and 12 regressors". Results, not presented here, for a sample of 88 countries and 18 variables for the period 1960-1996 from the datbase used in Fernàndez *et al.* (2001), show that four regimes appear, and that they are very similar to those discussed in this paper.

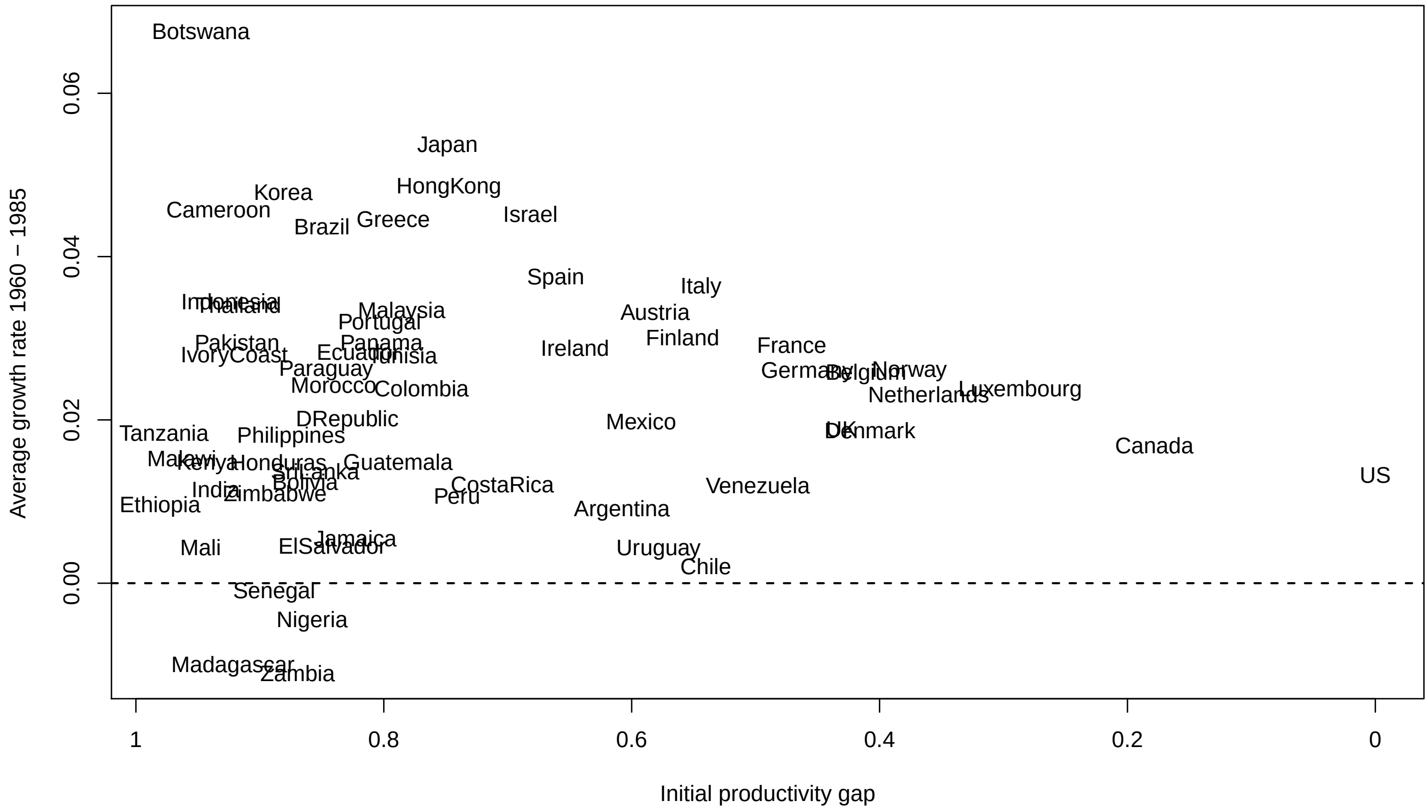

Figure 1: Relation between average growth rate and initial productivity

Figure 1 shows a "triangular" relation between growth rates and initial productivity levels, a relation found in other studies (see, e. g., Temple (1999), p. 117). This pattern reveals the absence of absolute convergence in this sample, as absolute convergence requires a negative relation between growth and initial productivity. At this stage, however, neither conditional convergence, nor the existence of nonlinear patterns of growth and growth regimes can be ruled out. We will show that our cluster analysis may help to clarify this point. Specifically, we will re-present this picture in Section 4.2, after the application of our clustering procedure.

Table 3 reports the pairwise correlations among the features.[20]

[20] We substituted the few lacking observations in our sample with the average value of the available observations for that feature. Some features (Trade, MinDep, Ores) were taken in logs, in order to make their distribution closer to the normal. The values of zero for the logged variable MinDep were substituted by small numbers, specifically: 0.5 X the minimum value present for MinDep in the database. See Table 14 in Appendix A.1 for more details.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
		G6085	LF6085	GGap60	PE60	SE60	GovC	Transp	Struct	ElMach	NoElMa	FreeS	Trade	MinDep	Ores	xConstIn
2	LF6085	-0.14	1													
3	GGap60	0.00	**0.44***	1												
4	PE60	**0.28**	**−0.43***	**−0.68***	1											
5	SE60	**0.22**	**−0.46***	**−0.72***	**0.82***	1										
6	GovC	-0.19	0.13	**0.29**	**−0.38***	**−0.38***	1									
7	Transp	**0.27**	**−0.25**	**−0.35***	**0.38***	**0.26**	0.04	1								
8	Struct	**0.33***	**−0.33***	**−0.40***	**0.61***	**0.58***	-0.18	**0.23**	1							
9	ElMach	**0.50***	**−0.25**	**−0.32**	**0.25***	**0.22**	-0.07	**0.60***	**0.25**	1						
10	NoElMa	**0.45***	**−0.34***	**−0.32**	**0.35***	**0.34***	0.16	**0.57***	**0.30**	**0.64***	1					
11	FreeS	**0.24**	**−0.44***	**−0.73***	**0.67***	**0.75***	**−0.27**	**0.42***	**0.41***	**0.50***	**0.49***	1				
12	Trade	0.18	0.06	-0.03	0.07	0.00	**0.26**	**0.30**	-0.02	**0.22**	**0.28**	0.13	1			
13	MinDep	-0.08	**0.24**	0.04	0.01	-0.02	0.00	0.01	0.12	0.05	0.05	0.03	-0.06	1		
14	Ores	-0.11	0.01	-0.08	0.02	0.05	0.05	0.19	0.1	0.04	0.09	0.03	0.05	**0.62***	1	
15	xConstIn	0.09	**−0.27**	**−0.44***	**0.36***	**0.54***	0.01	**0.34***	**0.35***	**0.39***	**0.46***	**0.60***	0.10	0.01	0.12	1
16	xConstAv	0.11	**−0.38**	**−0.58***	**0.47***	**0.64***	-0.06	**0.32**	**0.34***	**0.45***	**0.52***	**0.83***	0.11	-0.04	0.03	**0.83***

Table 1: Correlations among the features. Bold indicates significance at 10%, * at 1%

From the correlations in Table 3 we notice that: i) the three measures of institutional quality are highly correlated, the highest values being found for the correlations between the average value of constraints on the executive and its initial level, and with FreeS. The levels of the (negative) correlation of the institutional variables with the initial gap in productivity, however, are quite different: the highest degree of linear correlation is found when institutional quality is measured by FreeS, suggesting that the latter variable may be more properly be related to productivity. iii) The initial productivity gap shows no correlation with the growth rate, consistent with the lack of absolute convergence found in Figure 1. iv) The growth rate appears positively and significantly correlated with initial human capital, the components of equipment investment, and FreeS. The latter variable, therefore, appears more related to economic growth than the two alternative measures on institutions. v) Not surprisingly, initial primary and secondary education are highly correlated. In the next section we present the results of our empirical analysis.

4 Empirical Analysis

In this section we report the results of the application of the GM clustering algorithm. To check for the robustness of our results with respect to the definition of the variables measuring institutions and natural resources, we will perform four exercises based on different sets of variables, that will be respectively defined: Exercise 1, 2, 3, and 4 (Ex 1, Ex 2, Ex 3 and Ex 4 henceforth).[21]

[21] Specifically, with respect to the features' list in Table 14: Ex 1 is based on features (1) - (13); Ex 2 on features (1) - (10), (12), (13) and (15), i.e. considers xConstIn instead of FreeS to measure institutions; Ex 3 on features (1) - (10), (12), (13) and (16), i.e. considers xConstAv instead of FreeS to measure institutions; Ex 4 on features (1) - (12) and (14), i.e. considers Ores instead of MinDep to measure natural resource abundance.

In particular, we initially cluster the countries in the dataset, and show that the identified clusters are consistent with different growth regimes. Subsequently, for each growth regime we will: i) characterize the membership to a regime by the values of individual features; ii) characterize the relationships among the features *within* each cluster of countries. For the latter purpose, we will apply the GM algorithm to the features, i.e. we will treat the features as objects to be partitioned on the basis of the strength of their correlations.

Finding groups of similar countries is relevant to understand *which countries share a common growth model*, or belong to a growth regime (see, e. g., Durlauf and Johnson (1995)). The second step of our analysis, instead, aims at uncovering information on *the characteristics of such growth models*.

The GM clustering algorithm is designed for normally distributed variables, but are the variables in our sample normally distributed? Appendix B contains a discussion of this issue. Overall, departures from normality for most of the features do not appear severe. In any case, we compared the results from the application of the GM algorithm with those obtainable with other clustering techniques (see Appendix C.2), to check whether violation of the normality hypothesis for some variables indeed produces unreliable results, and for the more general purpose of checking the robustness of our results. Appendix C.2 shows that the results presented below are robust.[22]

4.1 Clustering the countries

Our first step consists in clustering the countries. We run the GM algorithm using simulated annealing (SA), and use the merging algorithm (MR) as control (see Giada and Marsili (2002), p. 655). Table 2 contains a summary of the results.

	SA		MR	
	# Clusters	Lik (Lik/N)	# Clusters	Lik (Lik/N)
Ex 1	16	35.502 (0.5818)	17	35.380 (0.5796)
Ex 2	16	35.075 (0.5747)	16	34.343 (0.5630)
Ex 3	16	34.465 (0.5646)	19	34.038 (0.5575)
Ex 4	17	32.879 (0.5390)	18	31.903 (0.5299)
DES	15	46.787 (0.7699)	15	45.872 (0.7525)

Table 2: Clustering of Countries: GM algorithm, comparison between SA and MR

Table 2 shows that the variable choice in Ex 1 produces slightly better results in terms of maximization of the likelihood function than those obtainable with alternative definitions of

Finally, we will also consider an exercise including features (1) - (10), i.e. the ten variables used by Desdoigts (1999), that will be labeled DES.

[22]Notice that in the main reference for this paper, i. e. Desdoigts (1999), no robustness tests of this sort are performed.

the variables measuring institutions and natural resources. The results, however, do not seem to be particularly affected by these alternative variable definitions. If we restrict the clustering exercise to the ten variables used by Desdoigts (1999), we obtain a smaller number of clusters and a higher value of the likelihood, indicating that the three variables that we added are little correlated with those used by Desdoigts (1999). Finally, using SA provides better results than MR.

Table 3 contains the details of the cluster structure that we obtain performing Ex 1.

Cluster 1, $n = 10$, $g = 0.8780$		Cluster 6, $n = 3$, $g = 0.9656$	
Italy	-1.4933	Peru	-1.4924
France	-1.4175	Bolivia	-1.0386
Germany	-1.2770	Philippines	-0.8893
Austria	-1.0740	Cluster 7, $n = 4$, $g = 0.9211$	
Greece	-0.9191	Malaysia	-0.9502
Portugal	-0.7825	DRepublic	-0.8337
Spain	-0.6348	Indonesia	-0.8116
Japan	-0.5980	Cluster 8, $n = 2$, $g = 0.9920$	
Ireland	-0.5789	Canada	-1.5446
Finland	-0.5622	US	-1.5446
Cluster 2, $n = 6$, $g = 0.9740$		Cluster 9, $n = 4$, $g = 0.7660$	
Netherlands	-1.9105	Colombia	-0.7543
Belgium	-1.7719	Mexico	-0.7329
Norway	-1.6745	Brazil	-0.5311
Denmark	-1.4533	India	-0.0274
Luxembourg	-1.2864	Cluster 10, $n = 3$, $g = 0.8645$	
UK	-0.7423	CostaRica	-0.9772
Cluster 3, $n = 5$, $g = 0.9634$		ElSalvador	-0.97723
Mali	-1.8885	Venezuela	-0.2509
Tanzania	-1.4029	Cluster 11, $n = 3$, $g = 0.8612$	
Ethiopia	-1.3768	Thailand	-0.8123
Malawi	-1.2072	Korea	-0.5983
Senegal	-0.5148	Paraguay	-0.5462
Cluster 4, $n = 4$, $g = 0.9177$		Cluster 12, $n = 4$, $g = 0.8283$	
Honduras	-1.2997	Chile	-0.7195
Morocco	-1.2520	Argentina	-0.6299
Tunisia	-0.7144	Ecuador	-0.3599
Guatemala	-0.2731	Cluster 13, $n = 5$, $g = 0.6556$	
Cluster 5, $n = 5$, $g = 0.8319$		Zambia	-0.5909
Kenya	-1.1367	Zimbabwe	-0.4505
IvoryCoast	-0.9041	Nigeria	-0.4126
Pakistan	-0.6218	Jamaica	-0.1227
Cameroon	-0.5540	Cluster 14, $n = 3$, $g = 0.6686$	
Madagascar	-0.2881	SriLanka	-0.5524
		Panama	-0.2274
		Uruguay	-0.1639

Table 3: Clustering with Ex 1 (GM/SA): 16 clusters

In Table 3 we report 14 clusters only, as the cluster structure also included two insignificant clusters, one containing Botswana and Hong Kong and the other containg Israel, which can therefore be considered as outliers in this exercise. For each cluster s we report the value of the parameter g_s which: "tunes the similarity of objects within cluster[s]" (Giada and

Marsili (2002), p. 655). The largest g_s, the higher the similarity of the objects within cluster s. In addition, for every object i in cluster s we report the value of $\Delta_{\mathcal{L}_c}$, which measures the contribution of country i to the likelihood. That is, $\Delta_{\mathcal{L}_c}$ quantifies the reduction in the likelihood that obtains if object i is removed from the clustering. For example, removal of Finland from the clustering would marginally affect the likelihood, i. e. the probability of observing our data as the realization of the stochastic process in Equation (1), with the parameters in Table 3, would marginally change. On the contrary, removal of Italy would affect the likelihood more significantly. In this way, we obtain a measure of the statistical significance of the membership to a cluster, and are able to rank countries within clusters according to the "strength" of their membership to a specific cluster.[23] The countries reported at the top of the clusters' country lists in Table 3 can therefore be considered as "representative countries" of that cluster.[24]

From Table 3 we notice that:

1. There are three clusters (Clusters 1, 2 and 8) containing OECD countries.[25] The degree of similarity within these clusters, measured by g_s, is however very different: it is about 0.99 in Cluster 8, which includes US and Canada; about 0.97 in Cluster 2, which includes North European countries; and about 0.88 in Cluster 1, which contains continental and Mediterranean European countries plus Japan, Ireland and Finland. Membership of the latter three countries to Cluster 1 is, however, weak.

2. Sub-Saharan countries tend to cluster. In particular, three clusters (3, 5 and 13) contain only or essentially Sub-Saharan countries. The degree of similarity measured by g_s is much higher in Cluster 3 which includes two subsets of geographically close countries,

[23] Giada and Marsili (2002), p. 653, show that the maximum likelihood of the cluster structure $\mathcal{S}$ can be expressed as $P(\mathcal{G}^*, \mathcal{S}|\vec{\xi_i}) \propto e^{D\mathcal{L}_c}$, where $D >> 0$. Hence, we can write the following relation between joint probabilities:

$$\frac{P(\vec{\xi_i}|\mathcal{G}^*, \mathcal{S}/\{i\})}{P(\vec{\xi_i}|\mathcal{G}^*, \mathcal{S})} = e^{-D\Delta_{\mathcal{L}_c}}.$$

On the assumption that $P(\vec{\xi_i}|\mathcal{G}^*, \mathcal{S}) \approx 1$, it obtains $P(\vec{\xi_i}|\mathcal{G}, \mathcal{S}/\{i\}) \approx e^{-D\Delta_{\mathcal{L}_c}}$. This magnitude can therefore be interpreted as the probability of observing our sample if the $i-$th object is not taken into account, relative to the probability of observing our sample when the $i-$th object is included. For example, these probabilities for countries in Cluster 1 such as Italy and Finland amount, respectively, to $3.71 \cdot 10^{-9}$ and $6.70 \cdot 10^{-4}$. In other words, although both probabilities are very small, if we do not consider Italy (Finland) in the clustering, it is much (little) more unlikely to observe our data as the realization of the stochastic process in Equation (1) with the parameters in Table 3. In this sense membership of Italy to Cluster 1 is more relevant than membership of Finland.

[24] In Appendix C.2.1 we show that there is a significant overlap between the set of these "representative countries" and the "exemplar countries" found by applying the clustering technique of Frey and Dueck (2007).

[25] The OEDC countries in our sample were among the founding members of OECD in 1961, with the exception of Japan and Finland which, respectively, joined the OECD in 1964 and 1969. Other OECD countries in our sample which, however, joined after the end of the period considered here, are Mexico (1994) and South Korea (1996). In Desdoigts (1999) Uruguay is wrongly indicated as an OECD country.

one from West Africa (Senegal and Mali) and one from East Africa (Ethiopia, Tanzania and Malawi).

3. Latin American and Asian countries are often found in the same cluster (Clusters 6, 7, 11 and 14), while Clusters 10 and 12 contain Latin American countries only, and cluster 9 contains Latin American countries and India, but the significance of the latter's membership is very low. In one case, Cluster 4, there appears a relatively high similarity between two neighbor Latin American countries (Honduras and Guatemala) and two Northern African countries (Morocco and Tunisia).

To sum up, we find that OECD countries are similar, but do not appear at this stage as part of one cluster. A difference emerges between North-America, Northern Europe and Central/Southern Europe. Desdoigts (1999) finds a significant separation of OECD from non-OECD countries and, within the former group, between Protestant and Catholic countries. Our results only partially confirm the latter finding. In particular, countries in Cluster 1 are essentially Catholic (exceptions being represented by Greece, Japan and Finland), but: in Cluster 2 we find three Protestant countries (Norway, Denmark and UK), two Catholic countries (Belgium and Luxembourg) and a country such as Netherlands with mixed religions,[26] while in Cluster 8 we find the US, having a relatively large fraction of Protestants, and Canada, having a relatively large fraction of Catholics.[27] Hence, at this stage only Catholic countries seem to cluster quite clearly, while a cluster of Protestant countries is far from clear (as, actually, it is also in Desdoigts (1999)). In addition, geographical proximity may play a role in Clusters 1 and 8.[28]

Sub-Saharan countries seem to display a relatively high degree of similarity but, again, not all the Sub-Saharan countries in our sample emerge like an individual cluster at this stage. Latin American countries tend to form homogeneous clusters, or heterogeneous clusters with Asian countries. There appears some similarity between Latin American countries and African Countries (represented by Clusters 4 and 13) and only one case in which there is similarity between African and Asian countries, represented by Pakistan in Cluster 5. In general, a partition based on geography is far from clear, a result that, for example, suggests some caution in the use of "regional" dummies in growth empirics.

[26] According to *Statistics Netherlands* (`http://www.cbs.nl`), in 2005/2006 in the Dutch population 29% declared to be Catholic, 19% Protestant, and 42% declared to have no religion.

[27] Although Protestant religion is relatively more diffused than Catholic in the US (approximately 43% vs 24% in 2001, see `http://www.census.gov`), from the 2001 Census 42% of Canadians declared to be Catholic, while only 24% declared to be Protestant (see `http://www.statcan.gc.ca`).

[28] US and Canada may also be similar in terms of ethnic fractionalization (Tan (2009), p. 10). See also Appendix C.2.2 for further discussion of this point based on the application of another clustering technique, which casts some doubts on the primacy of religion over OECD membership in the clustering of industrialized countries.

To check for the robustness of the cluster structure in Table 3 with respect to the features' definitions, we compared it with the cluster structures obtainable from Ex 2 - Ex 4, DES (using both SA and MR) and with the cluster structure originally found in Desdoigts (1999) (results are in Appendix C.1). In particular, after having checked robustness with respect to the use of MR instead of SA, the results from Ex 1 are compared with the other cluster structures in a rigorous manner by applying the methods of Rand (1971), Meilă (2007) and Zhou *et al.* (2005).[29] Results in Table 18 confirm that the robustness of the clustering from Ex 1 is high, and that the more relevant differences appear when this clustering is compared with that of Desdoigts (1999). Hence, although with respect to Desdoigts (1999), we do not find remarkable differences with respect to the OECD countries, the overall cluster structure that we obtain is rather different (see below for a further comparison).[30]

To check whether further structure can be identified in the data, we run the GM algorithm on the clusters in Table 3 (results will be labeled "2-step SA"). Table 4 contains the results for Ex 1, along with the control cluster structures from Ex 2 - Ex 4 and DES. Moreover, we report ALD.

[29] Details of these methods are provided in Appendix C.1.

[30] In Appendix C.1 we also present results for a test of similarity of the partitions DES and the cluster structure found in Desdoigts (1999), labeled ALD. We find that they are quite different, indicating the the inclusion of institutions, natural resources and trade, and the adoption of the GM algorithm, make the clustering found in Desdoigts (1999) not very robust.

	Country	Ex1	Ex2	Ex3	Ex4	DES	ALD
2	Austria	1	2	3	1	1	2
3	Belgium	1	2	3	1	1	1
8	Canada	1	2	3	1	1	1
12	Denmark	1	2	3	1	1	1
17	Finland	1	2	3	1	1	1
18	France	1	2	3	1	1	2
19	Germany	1	2	3	1	1	2
20	Greece	1	2	3	1	1	2
26	Ireland	1	2	3	1	1	2
28	Italy	1	2	3	1	1	2
31	Japan	1	2	3	1	1	1
34	Luxembourg	1	2	3	1	1	2
41	Netherlands	1	2	3	1	1	1
43	Norway	1	2	3	1	1	1
49	Portugal	1	2	3	1	1	2
51	Spain	1	2	3	1	1	2
56	UK	1	2	3	1	1	1
57	US	1	2	3	1	1	1
4	Bolivia	2	1	1	3	3	6
11	CostaRica	2	5	2	5	2	6
15	ElSalvador	2	5	2	5	2	5
21	Guatemala	2	1	1	4	2	6
22	Honduras	2	1	1	2	2	5
30	Jamaica	2	11	2	2	2	7
40	Morocco	2	1	1	2	2	4
42	Nigeria	2	11	2	2	2	5
47	Peru	2	1	1	3	2	6
48	Philippines	2	1	1	3	2	3
55	Tunisia	2	1	1	4	2	6
59	Venezuela	2	1	1	5	2	5
60	Zambia	2	11	2	2	2	4
61	Zimbabwe	2	11	2	2	2	6
1	Argentina	3	4	4	3	3	7
6	Brazil	3	4	1	3	4	6
9	Chile	3	4	4	3	3	5
10	Colombia	3	4	1	5	4	5
13	DRepublic	3	1	1	3	4	5
14	Ecuador	3	4	4	5	3	6
24	India	3	4	4	3	3	6
25	Indonesia	3	1	1	3	4	6
33	Korea	3	6	1	4	4	3
37	Malaysia	3	1	1	3	4	6
39	Mexico	3	4	1	3	4	5
46	Paraguay	3	1	1	5	4	5
54	Thailand	3	1	1	4	4	3
7	Cameroon	4	3	2	4	2	7
16	Ethiopia	4	3	2	2	2	6
29	IvoryCoast	4	3	2	2	2	4
32	Kenya	4	3	2	2	2	4
35	Madagascar	4	5	2	2	2	6
36	Malawi	4	3	2	2	2	4
38	Mali	4	3	2	2	2	4
44	Pakistan	4	3	2	4	2	6
50	Senegal	4	3	2	2	2	4
53	Tanzania	4	3	2	2	2	4
5	Botswana	13	3	6	4	0	7
23	HongKong	13	6	6	4	4	3
45	Panama	15	5	4	5	3	6
52	SriLanka	15	5	4	5	3	6
58	Uruguay	15	5	4	5	3	2
27	Israel	0	3	4	0	3	7

Table 4: 2-step clusterings from Ex 1, Ex 2, Ex 3, Ex 4, DES, ALD; SA

Table 4 shows that the clusters of Table 3 can be grouped in four larger clusters, with few countries remaining excluded.[31] In particular we find a cluster of OECD countries (Cluster 1, $g = 0.5817$); a cluster of Sub-Saharan countries, with the exception of Pakistan, (Cluster 4, $g = 0.6894$), and two mixed clusters: one containing only Latin American and Asian countries (Cluster 3, $g = 0.3303$), one containing one Asian country (Philippines), Latin American and African Countries, from both Northern and Sub-Saharan Africa (Cluster 2, $g = 0.3661$).

From the comparison with Ex 2 - Ex 4 and DES, we first of all notice the extreme robustness of the cluster of OECD countries: these countries are systematically grouped together. Similar, albeit not so strong, evidence is found for the countries in Cluster 4. Clusters 2 and 3, instead, appear somewhat more sensitive to the differences in the definition of the variables in Ex 2 - Ex 4, but quite robust to the use of the smaller number of variables in DES.[32]

To provide a more rigorous test for the robustness of the clustering from Ex 1, we compare the clusterings of Table 4 using the methods of Rand (1971), Meilă (2007) and Zhou *et al.* (2005), respectively indicated as *Rand*, *VI* and *Mall* (see Appendix C.1 for a brief description of these methods).[33]

Index (range)	Ex 2	Ex 3	Ex 4	Des	Ald
Rand (0 - 1)	0.1	0.13	0.14	0.12	0.2
VI (0 - 4.11)	0.21	0.19	0.29	0.17	0.6
Mall (0 - 120)	30	38	42	34	108

Table 5: Comparison between Ex1 and Ex2, Ex3, Ex4, Des, ALD. 2-step SA

Table 5 shows that the 2-step clustering from Ex 1 is quite robust, and that, again, the largest dissimilarity appears with respect to the cluster structure from Desdoigts (1999). If we compare DES and ALD, we obtain the values, respectively for *Rand*, *VI* and *Mall* of 0.27, 2.74 and 112. These values are relatively high compared to those in Table 5, confirming the remark in footnote 30 that the clusters of Desdoigts (1999) are not very robust.[34]

[31] In the remaining of the paper, we will consider as outliers Botswana, Hong Kong, Israel, plus Panama, Sri Lanka and Uruguay, being understood that the reason for considering the latter three countries as outliers is that they do not belong to one of the four clusters in Table 4.

[32] This result is also confirmed by the values of the parameter g in the four clusters. We also tried a further reclustering step, which provided the following results: with Ex 1, Ex 3, Ex 4 and DES no further clustering appears. With Ex 2 three clusters appear, but the values of the g's are very low (0.202, 0.174, 0.055).

[33] In all cases, a value of zero indicates that two cluster structures are identical.

[34] Appendix C.2 contains further robustness tests based on the utilization of other clustering techniques, namely that of Frey and Dueck (2007) and the more standard procedures described in Kaufman and Rousseeuw (1990).

4.2 Re-Examining the Growth Path

Now we reconsider the relationship between the growth rate and the initial productivity gap highlighting the cluster structure identified in the previous section. Figure 2 refers to the whole sample, while Figure 3 shows the growth patterns in the four clusters, ordered following the level of initial productivity.

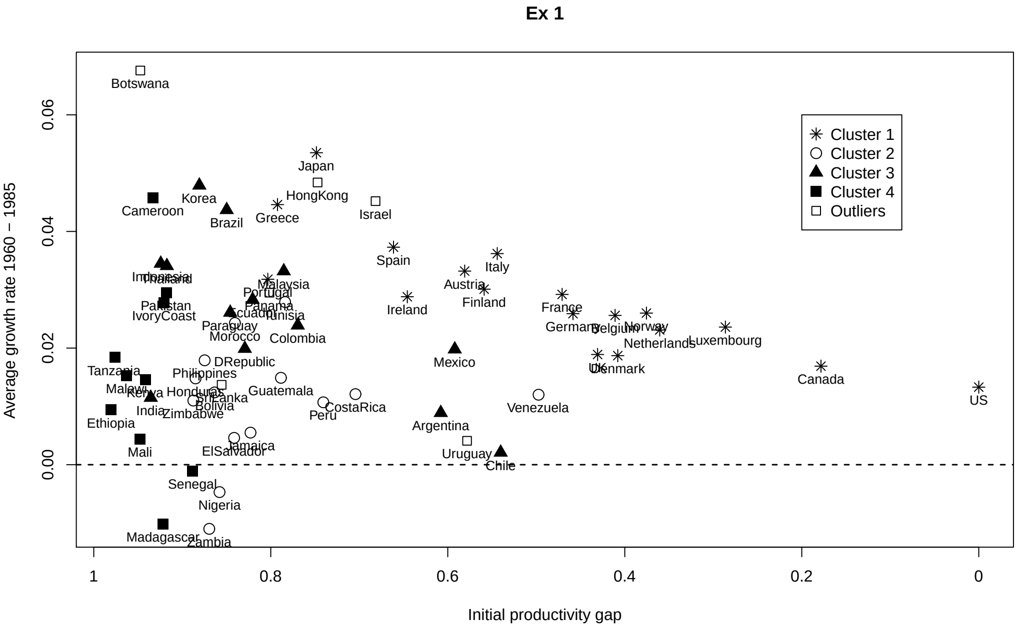

Figure 2: Relation between average growth rate and initial productivity: full sample

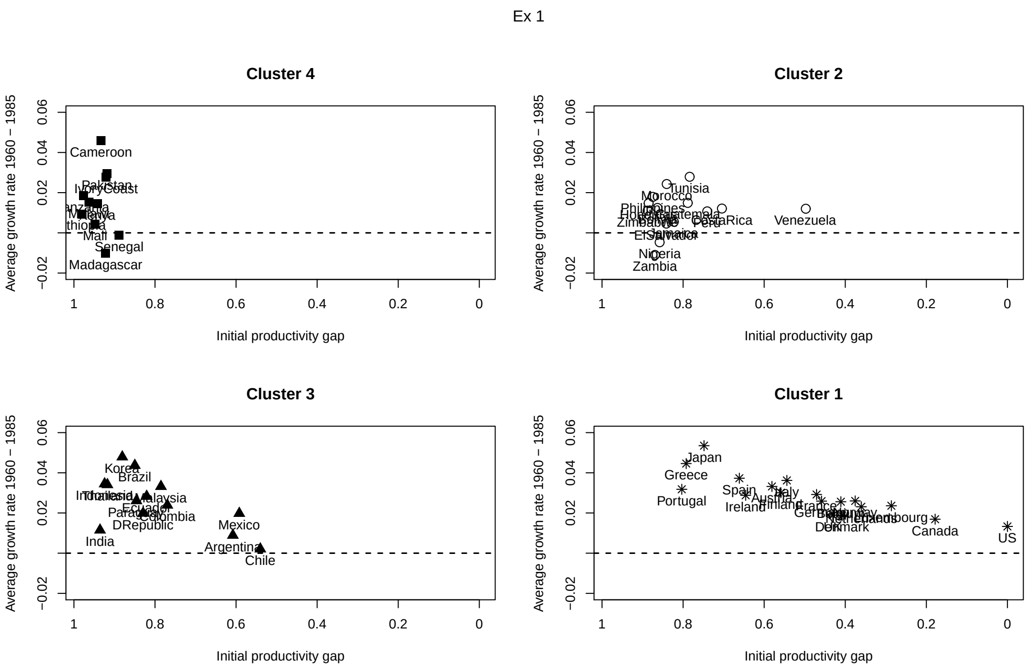

Figure 3: Relation between average growth rate and initial productivity: four clusters

Figures 2 and 3 suggest that the four clusters correspond to four growth regimes, in terms of the relationship between the growth rate and the level of (initial) productivity. Starting from the lowest levels of productivity, Countries in Cluster 4 show a very high variability in the growth rate and a uniformly low productivity level. Countries in Cluster 2, having on average an initial productivity level higher than Cluster 1, display both positive and negative growth rates, and some tendency to move onwards. Countries in Cluster 3 have a growth rate which appears on average significantly higher than in Cluster 2, and show some tendency to convergence among them.[35] Finally, countries in Cluster 1 show a clear tendency to convergence, displaying a negative relationship between initial productivity and growth.

These growth regimes are consistent with Fiaschi and Lavezzi (2003) who, using nonparametric methods, identified four growth regimes: an initial regime including a locally stable equilibrium (poverty trap), where growth is on average low and volatile; a second regime including an unstable equilibrium, where growth can be positive or negative; a third regime where growth is on average positive (the "accelerating growth" regime); a fourth regime where convergence takes place towards a stable high-income equilibrium.[36]

Hence, the growth path from lower productivity levels to the highest, suggested from our clustering exercise is (using clusters' labels to define growth regimes): $4 \rightarrow 2 \rightarrow 3 \rightarrow 1$.[37] In the next section, we characterize the four growth regimes in terms of the features used to identify them.[38]

4.3 Characterizing Growth Regimes

In this section we aim at characterizing growth regimes in terms of the features that contributed to their identification. We divide the analysis in two parts: in Section 4.3.1 we provide: i) descriptive statistics of the features within each cluster; ii) a comparison of the cluster structure of Ex 1 with the cluster structures obtained by removing each feature at the time from the clustering. Both steps provide information on the relevance of individual features. Specifically,

[35] In particular if we exclude India, which, as shown in Table 3 has a weak membership to Cluster 9, which is part of the larger Cluster 3.

[36] The main difference in this representation of the growth process is that in Fiaschi and Lavezzi (2003) all regimes are separated by thresholds in income levels, while in in Figure 2 the second and third regimes do not appear to differ in the range of initial productivity, but in terms of the growth rate. However, Fiaschi and Lavezzi (2003) utilize a much larger sample (120 countries for the period 1960-89), and pool the data for the analysis of the growth dynamics, allowing for a better identification of the growth path. Moreover, they define the growth regimes in terms of *relative per capita* income, that is per capita (not per worker) income normalized with respect to the sample mean.

[37] From now on we label growth regimes as the four clusters, and interchangeably use the two terms. We return below on the issue of whether transitions across regimes are expected to occur in this framework, in particular exits from Regime 4. As mentioned in the introduction, this possibility distinguishes models with or without poverty traps in the family of nonlinear growth models.

[38] Appendix D contains the graphical representations of the growth regimes with Ex 2, Ex 3, Ex 4 and Des, showing broad consistency with those presented in this section.

the first allows for comparisons of the features' levels in the different regimes; the second allows to identify the individual features' capacity to partition the sample of countries. Both pieces of evidence contribute to the identification of possible determinants of transitions across regimes.[39]

In Section 4.3.2, instead, we *cluster the features* within each growth regime. That is, we identify the optimal partition of the features based on the strength of their correlations. This piece of evidence aims at providing information of the growth model that applies within different regimes, not only in terms of the relation between the growth rate and initial productivity. We defer a full discussion of the results to Section 5.

4.3.1 On Individual Features

Figure 4 displays the average value and the standard deviation of the features in each of the four regimes. For each feature, we report a vertical bar for each regime, following the order: $4 \rightarrow 2 \rightarrow 3 \rightarrow 1$.

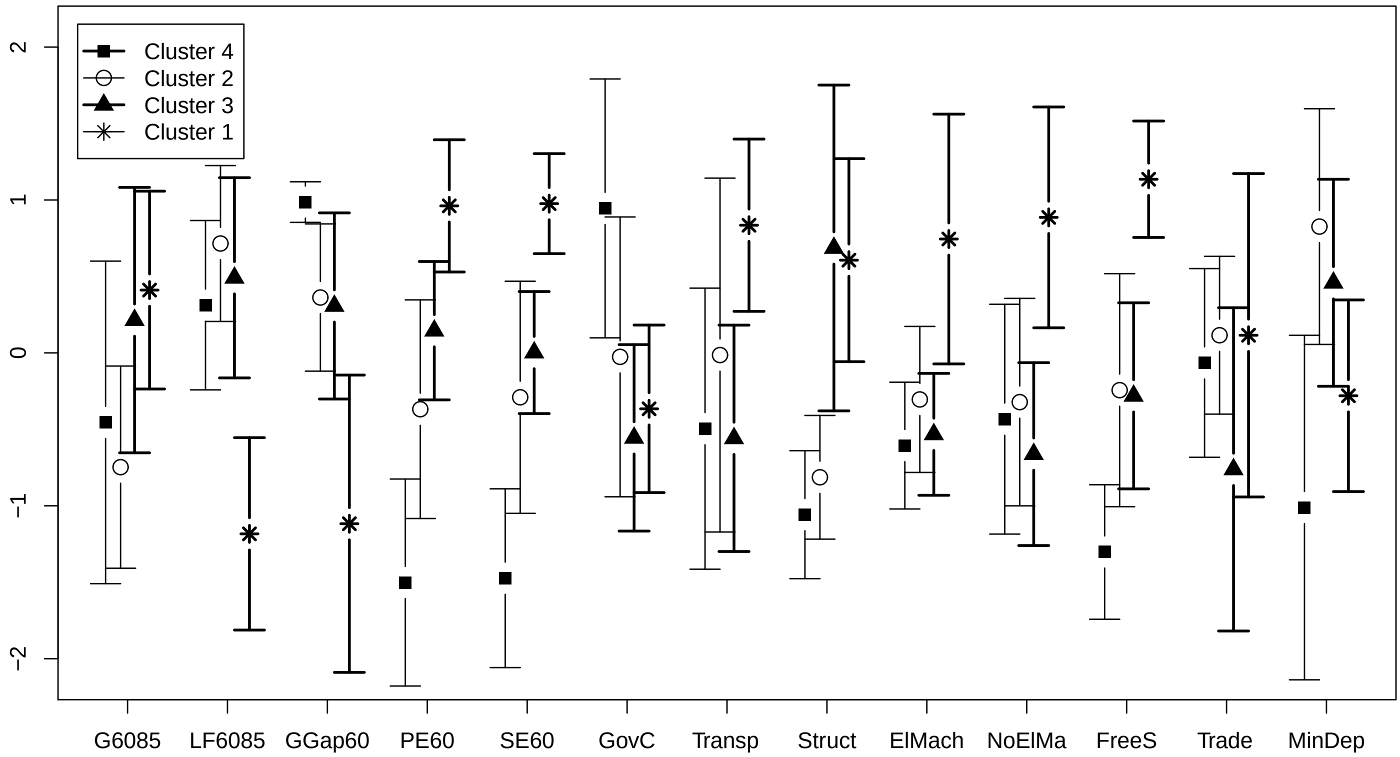

Figure 4: Average values and standard deviations of the features in Clusters 1 - 4, Ex 1, 2-step SA, ordered following: $4 \rightarrow 2 \rightarrow 3 \rightarrow 1$

Table 6 contains the p-values of tests of equality of the means of the features across clusters.

[39]As remarked, we refrain from making strong claims on causal relationships.

	G6085	LF6085	GGap60	PE60	SE60	GovC	Transp	Struct	ElMach	NoElMa	FreeS	Trade	MinDep
$4 \to 2$	0.45	0.09	**0.00**	**0.00**	**0.00**	**0.01**	0.27	0.17	0.11	0.71	**0.00**	0.46	**0.00**
$2 \to 3$	**0.00**	0.33	0.80	**0.03**	0.22	0.09	0.16	**0.00**	0.19	0.18	0.89	**0.01**	0.20
$3 \to 1$	0.50	**0.00**	**0.00**	**0.00**	**0.00**	0.38	**0.00**	0.81	**0.00**	**0.00**	**0.00**	**0.03**	**0.00**

Table 6: P-values of tests of equality of mean values in Figure 4. Bold indicates p-values smaller than 0.05

From the joint consideration of Figure 4 and Table 6, we can compare regimes following the sequence $4 \to 2 \to 3 \to 1$, representing different stages in the growth path. In particular, in comparing adjacent regimes, we find that:

- $4 \to 2$. The statistical significance of the difference in GGap60 indicates that the two growth regimes are significantly separated in terms of initial productivity. Moreover, countries in Cluster 2 have significantly higher levels of initial education, both primary and secondary, lower levels of public consumption, higher levels of institutional quality and *higher levels* of natural resources.[40]

- $2 \to 3$. With respect to countries in Cluster 2, countries in Cluster 3 have a (significantly) higher growth rate, higher primary education, higher investment rates in structures, and *lower* trade openness.

- $3 \to 1$. Countries in Cluster 1 have a significantly lower labor force growth rate, a lower initial productivity gap, higher initial education (primary and secondary), higher investment rates (in three components), higher institutional quality, higher trade openness, lower resource abundance.

To sum up: the relationship between initial education and growth regimes is almost monotonically increasing. On the contrary, physical capital appears especially relevant in characterizing high stages of development, with the exception of investment in Structures which appears important in distinguishing Cluster 2 from Cluster 3. Institutional quality is also increasing in the stages of growth, but not as initial human capital. A separation of growth regimes in terms of initial productivity clearly appears between 4 and 2 and 3 and 1, but not between 2 and 3.[41] Government consumption is relevant only in distinguishing regime 4 from 2, in particular through its reduction, while a reduction in labor force growth seems to matter only in distinguishing regime 3 from 1. Finally, trade openness and natural resources appear nonlinearly related to stages of growth.

In Tables 7 and 8 we compare the cluster structure of Ex 1 with the cluster structures obtained by running the clustering algorithm dropping one feature at the time. Specifically, in Table 7 we keep the clustering from Ex 1 fixed in a comparison with all the other cluster

[40] As remarked, this is not necessarily in contradiction with the "curse of natural resources" if we note that a higher stage of growth can be associated to more natural resources and better institutions.

[41] This, as noted, is in partial contrast with the growth regimes in Fiaschi and Lavezzi (2003).

structures. In Table 8 instead, we keep fixed each cluster structure obtained by dropping a feature. In this way, we first highlight the importance of individual features in separating the clusters of Ex 1,[42] then we focus on the alternative clusterings, highlighting the new groups that would form in each reclustering.

	Country	Ex1	G6085	LF6085	GGap60	PE60	SE60	GovC	Transp	Struct	ElMach	NoElMa	FreeS	Trade	MinDep
2	Austria	1	1	1	1	1	1	2	1	1	1	2	1	1	1
3	Belgium	1	1	1	1	1	1	2	1	1	1	2	1	1	1
8	Canada	1	1	1	1	1	1	2	1	1	1	2	1	1	1
12	Denmark	1	1	1	1	1	1	2	1	1	1	2	1	1	1
17	Finland	1	1	1	1	1	1	2	1	1	1	2	1	1	1
18	France	1	1	1	1	1	1	2	1	1	1	2	1	1	1
19	Germany	1	1	1	1	1	1	2	1	1	1	2	1	1	1
20	Greece	1	1	4	1	1	1	2	1	1	1	2	1	1	1
26	Ireland	1	1	1	1	1	1	2	1	1	1	2	1	1	1
28	Italy	1	1	1	1	1	1	2	1	1	1	2	1	1	1
31	Japan	1	1	1	1	1	1	2	1	1	1	2	1	1	1
34	Luxembourg	1	1	1	1	1	1	2	1	1	1	2	1	1	1
41	Netherlands	1	1	1	1	1	1	2	1	1	1	2	1	1	1
43	Norway	1	1	1	1	1	1	2	1	1	1	2	1	1	1
49	Portugal	1	1	1	1	1	1	2	1	1	1	2	1	1	1
51	Spain	1	1	4	1	1	1	2	1	1	1	2	1	1	1
56	UK	1	1	1	1	1	1	2	1	1	1	2	1	1	1
57	US	1	1	1	1	1	1	2	1	1	1	2	1	1	1
4	Bolivia	2	2	3	2	3	3	4	2	2	2	1	3	2	3
11	CostaRica	2	2	1	3	2	2	7	2	3	2	17	2	2	7
15	ElSalvador	2	2	2	3	2	2	1	2	3	2	1	2	2	3
21	Guatemala	2	2	16	5	2	2	1	2	2	2	1	2	2	2
22	Honduras	2	2	3	5	2	2	1	2	2	2	1	2	2	2
30	Jamaica	2	0	3	5	2	2	1	2	11	2	1	2	2	2
40	Morocco	2	2	3	5	2	2	1	2	2	2	1	2	2	2
42	Nigeria	2	2	3	5	2	2	1	2	11	2	1	2	2	2
47	Peru	2	2	3	2	3	3	4	2	2	2	1	3	2	3
48	Philippines	2	2	3	2	2	2	4	2	2	2	1	3	2	3
55	Tunisia	2	2	3	5	2	2	1	2	2	2	1	2	2	2
59	Venezuela	2	2	1	2	2	2	7	3	2	2	17	X	4	7
60	Zambia	2	3	3	5	2	2	1	4	11	2	1	2	2	2
61	Zimbabwe	2	2	3	5	2	2	1	2	11	2	1	2	2	2
1	Argentina	3	4	4	4	3	3	4	3	10	4	3	4	5	3
6	Brazil	3	4	4	2	3	3	4	3	2	4	3	3	4	3
9	Chile	3	4	4	4	3	3	4	3	2	4	3	4	5	3
10	Colombia	3	4	4	2	3	3	4	3	2	4	3	3	4	3
13	DRepublic	3	2	4	2	3	3	4	3	2	4	3	3	4	3
14	Ecuador	3	4	4	4	3	3	4	3	2	4	3	4	5	3
24	India	3	4	X	4	3	3	4	3	10	4	0	4	2	3
25	Indonesia	3	2	4	2	3	3	4	3	2	4	3	3	4	3
33	Korea	3	2	4	2	4	4	3	3	2	7	4	3	4	2
37	Malaysia	3	2	4	2	3	3	4	3	2	4	3	3	4	3
39	Mexico	3	4	4	2	3	3	4	3	2	4	3	3	4	3
46	Paraguay	3	2	4	2	4	4	3	3	2	7	4	3	4	3
54	Thailand	3	2	4	2	2	4	3	3	2	7	4	3	4	3
7	Cameroon	4	3	2	3	4	4	3	4	3	3	4	2	3	2
16	Ethiopia	4	3	2	3	2	2	1	4	3	3	1	2	3	2
29	IvoryCoast	4	3	2	3	2	4	3	4	3	3	4	2	3	2
32	Kenya	4	3	2	3	2	4	3	4	3	3	4	2	3	2
35	Madagascar	4	3	2	3	2	2	1	4	3	2	1	2	2	3
36	Malawi	4	3	2	3	2	2	3	4	3	3	1	2	3	2
38	Mali	4	3	2	3	2	2	1	4	3	3	1	2	3	2
44	Pakistan	4	3	2	3	4	4	3	4	3	3	4	2	3	3
50	Senegal	4	3	2	3	2	2	1	4	3	3	1	2	2	2
53	Tanzania	4	3	2	3	2	2	1	4	3	3	1	2	3	2
5	Botswana	13	3	16	5	4	4	3	13	15	3	4	18	3	2
23	HongKong	13	0	16	5	4	4	3	13	15	7	4	18	4	2
45	Panama	15	11	4	3	12	8	4	8	3	15	10	4	5	3
52	SriLanka	15	11	2	3	12	8	4	8	3	15	10	4	5	3
58	Uruguay	15	11	4	4	12	8	4	8	10	15	10	4	5	3
27	Israel	0	0	2	3	X	65	2	73	0	3	10	0	3	0

Table 7: Cluster robustness: each column contains the cluster structure that obtains each individual variable is dropped from the clustering. 2-step SA, Ex 1

[42]This exercise also represents a further robustness test for the clustering obtained applying the 2-step SA GM algorithm using the variables in Ex 1.

1 G6085		2 LF6085		3 GGap60		4 PE60		5 SE60		6 GovC		7 Transp		8 Struct		9 ElMach		10 NoElMa		11 FreeS		12 Trade		13 MinDep	
1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	4	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	4	1	1	1	1	1	1	1
1	1	2	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	4	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	4	1	1	1	1	1	1	1	4	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	4	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	4	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	4	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	4	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	4	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	4	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	2	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	2	1	1	1	1	1	1	1
1	1	2	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	2	1	1	1	1	1	1	1
2	2	4	2	2	2	2	2	2	2	1	2	2	2	2	2	2	2	1	2	4	2	2	2	13	2
2	2	2	2	3	2	2	2	2	2	1	2	2	2	3	2	2	2	1	2	2	2	2	2	4	2
3	2	4	2	3	2	4	2	4	2	1	2	2	2	3	2	2	2	1	2	2	2	2	2	4	2
2	2	0	2	3	2	2	2	2	2	1	2	2	2	3	2	2	2	1	2	4	2	2	2	2	2
2	2	4	2	3	2	2	2	2	2	1	2	2	2	3	2	2	2	1	2	2	2	2	2	2	2
2	2	4	2	3	2	4	2	2	2	0	2	2	2	3	2	2	2	1	2	2	2	3	2	13	2
3	2	4	2	3	2	2	2	4	2	1	2	2	2	2	2	4	2	1	2	4	2	2	2	4	2
3	2	4	2	3	2	4	2	4	2	1	2	2	2	2	2	2	2	1	2	2	2	4	2	2	2
3	2	4	2	3	2	4	2	4	2	1	2	2	2	3	2	2	2	1	2	4	2	2	2	4	2
2	2	4	2	2	2	4	2	2	2	1	2	2	2	3	2	2	2	1	2	4	2	2	2	3	2
2	2	4	2	2	2	4	2	2	2	1	2	2	2	3	2	2	2	1	2	4	2	2	2	4	2
3	2	15	2	3	2	2	2	2	2	1	2	2	2	3	2	2	2	1	2	4	2	2	2	4	2
2	2	4	2	2	2	2	2	4	2	1	2	3	3	2	2	2	2	1	2	2	2	4	2	2	2
2	2	2	3	4	3	2	2	4	2	1	2	3	3	3	2	2	2	1	2	2	2	2	2	2	2
3	2	2	3	2	3	4	2	2	2	1	2	3	3	2	2	2	2	1	2	4	2	2	2	4	2
2	2	2	3	2	3	4	2	2	2	13	3	3	3	2	2	13	3	1	2	4	2	2	2	4	2
2	2	2	3	4	3	3	2	2	2	4	3	3	3	3	2	4	3	1	2	4	2	13	3	2	2
2	2	2	3	0	3	2	2	2	2	13	3	3	3	2	2	4	3	1	2	2	2	4	3	2	2
13	3	2	3	4	3	2	2	3	3	4	3	3	3	2	2	0	3	3	3	2	2	4	3	2	2
4	3	2	3	4	3	2	2	2	3	4	3	3	3	4	3	4	3	3	3	2	2	0	3	3	3
4	3	2	3	4	3	2	2	3	3	3	3	3	3	2	3	4	3	3	3	2	3	4	3	2	3
4	3	2	3	4	3	3	3	3	3	4	3	3	3	2	3	4	3	3	3	3	3	4	3	3	3
4	3	2	3	4	3	2	3	3	3	4	3	3	3	4	3	4	3	3	3	3	3	4	3	3	3
4	3	3	4	4	3	3	3	3	3	3	3	3	3	4	3	4	3	3	3	3	3	4	3	3	3
4	3	3	4	15	3	3	3	3	3	3	3	3	3	4	3	4	3	3	3	3	3	4	3	3	3
4	3	3	4	4	3	3	3	3	3	3	4	2	3	4	3	4	3	3	3	3	3	4	3	3	3
4	3	3	4	15	3	3	3	3	3	2	4	4	4	4	3	3	4	3	3	3	3	3	4	2	3
4	3	3	4	4	3	3	3	3	3	3	4	4	4	4	3	3	4	13	4	3	3	3	4	3	3
4	3	3	4	3	4	3	3	3	3	3	4	4	4	4	3	3	4	4	4	3	3	3	4	3	3
2	3	1	4	3	4	3	3	2	3	3	4	4	4	15	3	3	4	13	4	2	3	13	4	4	3
3	4	3	4	3	4	3	3	13	4	3	4	4	4	4	3	3	4	4	4	2	3	3	4	3	3
3	4	3	4	3	4	3	3	4	4	3	4	4	4	15	3	3	4	4	4	3	3	3	4	3	3
3	4	3	4	15	4	2	3	13	4	3	4	4	4	4	3	3	4	3	4	3	4	3	4	4	3
3	4	3	4	13	5	13	4	4	4	3	4	4	4	3	10	3	4	4	4	3	4	3	4	15	3
3	4	15	4	2	5	4	4	4	4	3	4	4	4	3	10	3	4	3	4	3	4	3	4	3	3
3	4	3	4	2	5	13	4	3	4	3	4	4	4	15	10	3	4	3	4	3	4	3	4	2	3
3	4	1	4	13	5	3	4	4	4	15	4	2	4	2	11	13	7	0	10	15	4	2	4	2	3
15	11	3	4	2	5	4	4	3	4	2	4	15	8	2	11	3	7	15	10	15	4	3	5	15	3
15	11	15	4	2	5	3	4	3	4	2	4	15	8	2	11	3	7	15	10	15	4	3	5	3	3
15	11	13	16	2	5	15	12	15	8	15	4	15	8	2	11	3	7	15	10	13	18	3	5	15	3
13	0	2	16	2	5	15	12	15	8	15	4	13	13	13	15	15	15	2	17	13	18	15	5	2	7
0	0	13	16	2	5	15	12	15	8	2	7	13	13	13	15	15	15	2	17	2	X	15	5	2	7
2	0	3	X	2	5	0	X	0	65	2	7	0	73	0	0	15	15	3	0	0	0	15	5	0	0

Table 8: Cluster structures: dropping of individual variables. For every feature, each couple of columns reports the clustering reordered with respect to that feature (right column) and the clustering from Ex 1 (left column)

Table 7 shows that: i) Cluster 1 is extremely robust. Removal of individual features leaves the cluster structure unaffected, with the only exception of labor force growth; ii) Cluster 4 is also quite robust, as most or all the countries it comprises remain clustered together when individual features are dropped. iii) Clusters 2 and 3 appear somewhat more sensitive to the dropping of features, as only a few times most or all their member countries remain clustered. This result is a further proof of robustness of the cluster structure identified with Ex 1, in addition to those presented in Tables 4 and 5.

Table 8, as the results in Table 6, helps to identify role of individual features in the clustering. With respect to the statistically significant differences showed in Table 6, they show that:

1. $4 \rightarrow 2$. Removal of, alternatively, PE60 (column 4), SE60 (column 5), GovC (column 6), FreeS (column 11), MinDep (column 13), generates a new cluster which includes countries from Clusters 4 and 2.

2. $2 \rightarrow 3$. Removal of, alternatively, G6085 (column 1), PE60 (column 4) and Struct (Column 8), generates a new cluster including countries from Clusters 2 and 3. Removal of Trade (Column 12) does not exert such effect, with very little mixing of countries from Clusters 2 and 3.

3. $3 \rightarrow 1$. Removal of LF6085 (column 2) generates a new cluster (labeled 4), in which two countries of Cluster 1 (Greece and Spain) join Cluster 3. Removal of the other variables which appeared significant in Table 6, however, has not a similar effect.[43]

The statistical significance of a difference in Table 6, refers to a feature evaluated in two subgroups, and taken at its average value. Differently, the role of individual features when dropped refer to the capacity of that feature to affect all countries in the sample. For comparisons between regimes 4 and 2, and between 2 and 3, we see that these two criteria provide essentially the same results. On the contrary, when considering differences between 3 and 1, we can observe that a significant difference in the means can be a necessary but not sufficient condition for a feature to be relevant in altering the cluster structure.[44] In the next section we focus on features' correlations within each growth regime.

4.3.2 On Features' Correlations: Clustering the Features

From Figure 4 and Tables 6, 7, 8 we provided information on how individual features characterize the membership to the clusters. Now we investigate the relationship *among the features* in the whole sample and within each cluster. This part of the analysis is close in spirit to papers

[43]Table 7 also shows that: i) removal of GovC generates a new cluster in which Israel, an outlier, joins Cluster 1; ii) removal of LF6085 causes two countries from Cluster 2, Costa Rica and Venezuela, to join Cluster 1. The latter piece of evidence highlights that few transitions may follow a sequence of growth regimes different from the one suggested so far.

[44]Given the different nature of these two comparisons, we leave open this aspect for further research.

such as Durlauf and Johnson (1995) and Papageorgiou and Masanjala (2004), who clustered a sample of countries on the basis of initial conditions, and then estimated growth regressions within each subgroup. Evidence in favor of multiple growth regimes in that framework is represented by statistically different parameters across clusters of countries. Further, the presence of a negative relationship between initial income and the growth rate in a subgroup of countries would be evidence of *club convergence*, that is convergence to a common steady state for countries with similar parameters *and* initial conditions.

Our procedure aims at uncovering information on the structure of the correlations among the features within each cluster, in particular on the strength of the correlations among unspecified subsets of features. That is, when we find that two or more features belong to the same cluster, they are not only correlated, but their correlation endogenously emerges from an optimal partition of the set of features which, in principle, may combine in many different ways. To the best of our knowledge this is the first attempt to find an endogenous partition of variables by applying a clustering algorithm.

Also, our exercise goes in the direction suggested by Masanjala and Papageorgiou (2009), of searching for different growth models across subgroups of countries. The difference with respect to Masanjala and Papageorgiou (2009) is that we do not impose any exogenous splitting of the sample (Sub-Saharan African vs Non-African in their case), but resort to the cluster structure previously identified in which, in fact, not all Sub-Saharan countries fall in the same cluster.

Let us remark that in the process of clustering the features, we allow the growth rate to be on the same level of the other features. That is, we do not impose or assume the structure of a (linear) regression, in which an endogenous variable, the growth rate, is related to a set of exogenous variables, the growth regressors. Renouncing to this classification allows us nonetheless to obtain a relevant piece of information: the fact that the growth rate results associated to one or more variables (or even none) will be a result in itself, revealing different degrees of the strength of association of growth with some other variable.

We begin by clustering the features in the whole set of countries, and present the results in Table 9.[45] Results refer to Ex 1, the robustness tests with Ex 2 - Ex 4 and DES are presented in Appendix E.

Cluster All.I, g = 0.9364		Cluster All.II, g = 0.7164	
-SE60	-1.2553	ElMach	-0.6895
-PE60	-1.0141	NoElMa	-0.6231
-FreeS	-0.9584	Transp	-0.4008
GGap60	-0.9097	G6085	-0.1246

Table 9: Clusters of features: all countries. Ex 1

[45] We consider for the clustering both the values of the features and their negative values, in order to consider both positive and negative correlations: if a feature AAA is in the same cluster of feature BBB it means that there is a *positive* association/correlation. If feature AAA is in the same cluster of feature $-BBB$ it means that there is a *negative* association/correlation.

In the whole sample, we found five clusters of features, but report in Table 9 the most significant two.[46] In particular: in Cluster All.I there appears a quite strong negative correlation between the initial productivity gap, the two human capital variables and the quality of institutions. That is, the further (closer) the country from the productivity level of the US, the lower (higher) its initial human capital level and the quality of its institutions. Cluster All.II shows a positive correlation among three components of investment and the growth rate of productivity, a finding consistent with the main result of De Long and Summers (1991). Notice that, as predictable, no evidence of convergence emerges as there does not appear a positive correlation between the growth rate and the initial productivity gap.

In Tables 10, 11, 12, and 13, we present the clusterings of the variables in each cluster of countries from Ex 1, following the order 4 $\rightarrow$ 2 $\rightarrow$ 3 $\rightarrow$ 1 from which it emerges that what is observed for the full sample does not generally characterize the individual clusters. Table 10 contains the results for Cluster 4.

Cluster 4.I, g = 0.9301		Cluster 4.II, g = 0.9892		Cluster 4.III, g = 0.6622		Cluster 4.IV, g = 0.9391		Cluster 4.V, g = 0.8477	
-FreeS	-1.1388	ElMach	-1.4196	Transp	-0.6980	LF6085	-0.7677	GovC	-0.4754
GGap60	-0.9112	NoElMa	-1.4196	PE60	-0.3947	Struct	-0.7677	MinDep	-0.4754
-SE60	-0.5768			Trade	-0.2954				
				G6085	-0.1906				

Table 10: Clusters of features: Cluster 4. Ex 1

In Cluster 4 we found 5 clusters of features. In Cluster 4.I we have a negative correlation between the initial productivity gap, institutions and secondary education. This cluster is very similar to Cluster All.I, with the exception that initial primary education is excluded. In Cluster 4.II we find a strong association between the two machinery components of investment. In Cluster 4.III there appears a positive, albeit quite weak, association between the investment component in Transport, primary education, trade openness and growth. Cluster 4.IV contains the investment component in Structures and labor force growth, while cluster 4.V shows a positive correlation between government consumption and natural resources. The positive correlation between government spending and natural resources is consistent with the description provided by Auty and Gelb (2001), p. 135, of “the political economy of overspending” in some resource-rich countries: ”[p]olitical competition for rents, combined with non-transparent mechanisms of redistributing them ... makes it more difficult for governments to moderate spending levels”.

Table 11 contains the results on the clusters of features in Cluster 2.

[46] The three less significant clusters include, respectively, LF6085 and -Struct (g=0.4496), GovC and Trade (g=0.3276), and MinDep in an isolated cluster.

Cluster 2.I, g = 0.9699		Cluster 2.II, g = 0.7731		Cluster 2.III, g = 0.9191		Cluster 2.IV, g = 0.9087		Cluster 2.V, g = 0.8883	
ElMach	-1.4726	GGap60	-0.6498	PE60	-0.6731	GovC	-0.6338	Struct	-0.5701
Transp	-1.2438	-FreeS	-0.4678	SE60	-0.6731	Trade	-0.6338	MinDep	-0.5701
NoElMa	-0.8929	-LF6085	-0.2946						

Table 11: Clusters of features: Cluster 2. Ex 1

In Cluster 2 we find six clusters, including an isolated cluster represented by G6085. In Table 11 we observe: a strong cluster with three components of investment, a cluster with the two components of human capital, a cluster in which government consumption and trade openness are positively correlated, a cluster including the Structure component of investment and natural resources, and a cluster showing a negative association between the initial productivity gap and institutions. To summarize, we notice that in this cluster the growth rate does not seem to be strongly correlated with any explanatory variable, and that the initial productivity gap appears negatively correlated with the quality of institutions, but not with initial human capital.

Table 12 contains the results for Cluster 3.

Cluster 3.I, g = 0.6980		Cluster 3.II, g = 0.6769	
G6085	-0.7224	-Struct	-0.6062
Transp	-0.5736	GGap60	-0.5753
NoElMa	-0.5389	-PE60	-0.2605
LF6085	-0.3331	-SE60	-0.2270
ElMach	-0.2885		

Table 12: Clusters of features: Cluster 3. Ex 1

In Cluster 3 we find four clusters of features, In Table 12 we report the most significant two.[47] In Cluster 3.I we find a positive correlation between the growth rate and three out of four components of investment, as in Cluster All.II. In Cluster 3.II we have a negative correlation between the initial productivity gap, the two human capital variables and the remaining investment component. In this cluster, therefore, we find the positive association between investment and growth that we also found for the whole sample and that, as remarked, is consistent with the main result of De Long and Summers (1991). This piece of evidence suggests that a result that applies on average to the whole sample, may depend on a tendency present in a subsample only (see Durlauf and Johnson (1995) for a similar criticism of the results of Mankiw *et al.* (1992)). In addition: within this cluster the three initial conditions are in the same cluster highlighting, differently from the other clusters, a particularly strong correlation among them; FreeS is not negatively correlated to the initial productivity gap, indicating that, *within* this cluster institutional quality ceases to be correlated with initial productivity.

[47] We omit two weak clusters including, respectively, GovC and MinDep (g=0.3550), FreeS and Trade (g=0.3187).

Cluster 1.I, g = 0.9802		Cluster 1.II, g = 0.5866		Cluster 1.III, g = 0.6442	
G6085	-1.1787	FreeS	-0.4748	GovC	-0.2345
GGap60	-1.1787	SE60	-0.4140	-Struct	-0.2345
		ElMach	-0.2960		
		Transp	-0.1299		

Table 13: Clusters of features: Cluster 1. Ex 1

In Cluster 1, i.e. the cluster of OECD countries, we find five clusters of features, and report in Table 13 the most significant three.[48] By far, the strongest association that endogenously emerges is a negative correlation between the growth rate and the initial productivity gap. Other relatively relevant correlations are between secondary education, institutions, and two components of investment (positive, Cluster 1.II), and between government consumption and one component of investment (negative, Cluster 1.III). The first piece of evidence highlights that the strength of the forces of convergence in this cluster overwhelms the correlation found so far among the initial productivity gap, initial human capital and institutional quality. Secondary education and institutions, however, appear positively related (in Cluster 1.II their contribution to the likelihood is in particular higher than those of the two components of investment). Finally, Cluster 1.III suggests the possible presence of crowding out of one component of private investment by public expenditure.

In the next section we provide a discussion of these results, and those of the previous sections.

5 Discussion

From the results presented, the following picture of the growth process emerges. Economic growth is a highly nonlinear process which proceeds by stages, or growth regimes, in which the relationship between the growth rate and initial productivity varies. Different growth regimes are characterized by different values of the features, and transitions across different regimes are likely to depend on different features, although higher levels of human capital and of institutional quality emerge as relevant factors at all stages. The correlation among the features within the growth regimes is also different.

In the first growth regime, i.e. at the lowest productivity levels, we find Sub-Saharan Countries. Their growth rate is on average low and volatile. They are characterized by very low and uniform levels of human capital and of institutional quality (i.e. democracy),[49] and high levels of government consumption. It appears that possible transitions to the second growth regime (or Cluster 2) may be favored by more human capital, better institutions, less government consumption and more natural resources. The latter results contradicts the standard hypothesis

[48]The other two weak clusters contain, respectively, MinDep, LF6085 and -Trade (g=0.3564), and PE60 and -NoElMa (g=0.1147).

[49] Acemoglu *et al.* (2003) find that low-quality institutions are associated to high growth volatility.

on the curse of natural resources (Sachs and Warner (1995b)), but is consistent with Boschini *et al.* (2007) who claim that more natural resources *and* better institutions can favor growth. The clustering of the features in Table 10 shows that, *within* the countries in Cluster 4, the growth rate is weakly associated to Trade, PE60 and Transp, and that the initial productivity gap is larger the lower is the level of FreeS and SE60. No evidence of convergence is found.[50]

In the second growth regime (Cluster 2), we find at a higher initial average productivity level countries from (Northern and Sub-Saharan) Africa, Asia, and Latin America. They display positive and negative growth rates.[51] Possible transitions to the third growth regime (Cluster 3), may be favored by higher secondary education, higher investments in structures, and *less* trade openness.[52] Within this regime, no evidence of convergence is observed either. In addition, the growth rate does not appear strongly correlated to any feature (Table 11), while the initial productivity gap appears negatively correlated with institutional quality.

In the third growth regime (Cluster 3) we find Asian and Latin American countries showing on average a statistically higher growth rate than countries in Cluster 2. A weak tendency to convergence appears from Figure 3, third panel, but it is not detected in the analysis of Section 4.3.2. Transitions to the first growth regime appear to especially depend on lower labor force growth.[53] Within this cluster, three components of investment correlates well with growth, while the productivity gap is negatively correlated with the two human capital variables.

Finally, in the fourth growth regime (Cluster 1) we find OECD countries. The most striking characteristic of this cluster that endogenously emerges is the tendency for convergence. In other words, at this stage of development, the productivity gap appears to be the strongest predictor of economic growth. Whether this occurs for technological catching up (Abramowitz (1986)), or for decreasing returns from capital accumulation (Solow (1956)), cannot be clarified by the present analysis. This result is in contrast with Durlauf and Johnson (1995) and Papageorgiou and Masanjala (2004) who do not find evidence of convergence in the cluster of developed economies they identify, but is consistent with Dowrick and Nguyen (1989). Within this cluster,

[50]Some explanation on the claims on the role of individual features in transitions across regimes is needed. The growth regimes are defined in Figures 2 and 3 on the basis of *initial* productivity in 1960 and the growth rate in the period 1960-1985. Two features refer to initial conditions (PE60 and SE60), while the others refer to averages over the period 1960-1985. With respect to differences across growth regimes in terms of PE60 and SE60, we can make a simple claim such as: having more initial primary education would have contributed, cœteris paribus, to place a country from regime 4 in regime 2 in the period of interest. Differently, with respect to differences in terms of variables such as GovC, we can make a claim based on the following reasoning: if countries in regime 4 reduce the level of GovC to the level that characterized regime 2 in 1960-85, and maintain it afterwards, then, cœteris paribus, this would contribute to place them in regime 2 in a subsequent period.

[51]The growth rate in Cluster 2 is however on average negative, and lower than in Cluster 1, although the difference is not statistically significant

[52]Although trade openness does not appear relevant in Table 8.

[53]In Table 6 we found that increase in trade openness can favor transitions from regime 3 to regime 1. Albeit not confirmed in Section 4.3.1 when Trade was dropped from the clustering, this would suggest that, in contrast with, e. g. Frankel and Romer (1999), trade openness may favor growth only at certain stages.

moreover, secondary education is correlated with institutional quality. Membership to this growth regime appears so strong, and the features so strongly correlated, that basically the removal of no individual feature is able to split this cluster. The only exception, consistent with the result for Cluster 3, refers to labor force growth.

A final caveat regards the existence of multiple equilibria, in particular of a poverty trap. Our results identify which factors are associated to different growth regimes, suggesting their possible roles in transitions across regimes. In Figure 5 we present the distribution dynamics of productivity from 1960 to 1985.[54]

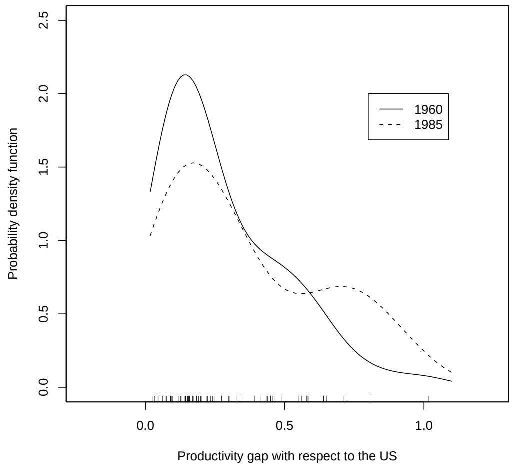

Figure 5: Distribution dynamics of the productivity gap, 1960-1985

Figure 5 shows that the productivity distribution dynamics of the countries in our sample displays a tendency for polarization, providing support to the existence of multiple equilibria. From this evidence, and the previous results, we can claim that there is persistence at low productivity, and therefore that escaping the bottom of the distribution can be problematic. Also, we can reject the hypothesis of conditional convergence à la Solow (1956), given that we find a dynamics compatible with this hypothesis in Cluster 1 only, which, depending on initial conditions also, should be defined as "club convergence". However, given the short time span covered by our analysis, we cannot fully reject the hypothesis that permanence in different regimes is temporary, as argued in particular by Galor (2007).

6 Concluding Remarks

In this paper we applied a clustering algorithm, based on the Maximum Likelihood principle, to a dataset on economic growth in a sample of countries. In the first stage of our analysis

[54]The values of the productivity gap in 1985 are simply computed by applying G6085 as an exponential growth rate to the initial productivity levels. The densities are estimated using a normal kernel and normal optimal smoothing parameter. See Bowman and Azzalini (1997), p. 31, for details.

we identified clusters of *similar* countries, which endogenously formed according to a set of *features*. We have identified four large clusters, and have shown that they are consistent with four different growth regimes. Human capital and institutions, at the core of much of current research and controversies, seem to play an important role at all growth stages, while other factors (e.g. physical capital, labor force growth, natural resources) at some stages only. Finally, convergence characterizes developed countries only.

Hence, although we provided support to theories of nonlinear growth, further analysis should be carried out to corroborate our results. In particular, the main limitation of the present analysis is the lack of a fully specified analysis of causality and of the dynamics of transitions across regimes. However, with respect to these fundamental issues, we have provided directions where the relevant causal and dynamic relationships are likely to be found.

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A Data

In this appendix we present the description of the variables used in this paper and the country list.

A.1 Variables

Table 14 contains the details on the data used in this paper.

Number	Name	Description
(1)	G6085	Average (1960-85) growth rate of productivity. Source: Desdoigts (1999) and De Long and Summers (1991)
(2)	LF6085	Average (1960-85) growth rate of labor force. Source: Desdoigts (1999) and De Long and Summers (1991).
(3)	GGap60	Initial productivity gap with respect to US. Source: Desdoigts (1999) and De Long and Summers (1991))
(4)	PE60	Primary Education: initial level in 1960. Source: Desdoigts (1999) and De Long and Summers (1991)
(5)	SE60	Secondary Education: initial level in 1960. Source: Desdoigts (1999) and De Long and Summers (1991). LOG
(6)	GovC	Average (1960-85) share of government consumption on GDP. Source: Desdoigts (1999) and De Long and Summers (1991)
(7)	Transp	Average (1960-85) share of investment in transport equipment on GDP. Source: Desdoigts (1999) and De Long and Summers (1991).
(8)	Struct	Average (1960-85) share of investment in structure on GDP. Source: Desdoigts (1999) and De Long and Summers (1991).
(9)	ElMach	Average (1960-85) share of investment in electrical machinery on GDP. Source: Desdoigts (1999) and De Long and Summers (1991)).
(10)	NoElMa	Average (1960-85) share of investment in non electrical machinery on GDP. Source: Desdoigts (1999) and De Long and Summers (1991).
(11)	FreeS	Average level of freedom. The index is based on the average of the scores for Civil Liberties and Political Rights (1: high, 7: low). This value is subtracted from 7 so the index reads as: 0 (low) - 6 (high). Data availability: 1972-1985. Source: Freedom House (2007). Missing data: Hong Kong
(12)	Trade	Sum of exports and imports of goods and services measured as a share of gross domestic product. Data availability: 1965-1985. Source: World Bank (2006). LOG
(13)	MinDep	Mineral depletion (% of GNI) Mineral depletion is equal to the product of unit resource rents ("world price minus country-specific extraction costs", Atkinson and Hamilton (2003), p. 1797) and the physical quantities of minerals extracted. It refers to bauxite, copper, iron, lead, nickel, phosphate, tin, zinc, gold, and silver. Data availability: 1970-1985. Source: World Bank (2006). Missing Data: Ivory Coast, Luxembourg, Malawi, Mali, Panama, Paraguay, Uruguay. LOG
(14)	Ores	Ores and metals exports (% of merchandise exports) Ores and metals comprise the commodities in SITC sections 27 (crude fertilizer, minerals nes); 28 (metalliferous ores, scrap); and 68 (non-ferrous metals). Data availability: 1962-1985. Source: World Bank (2006). Missing data: Botswana, Ethiopia, Luxembourg LOG
(15)	xConstIn	Executive constraint, initial value. Range: 1 (unlimited authority) - 7 (executive Parity or Subordination). Data availability: most countries 1960-1985. Some with different initial year: Botswana: 1966, Kenya: 1963, Madagascar: 1961, Malawi: 1964, Pakistan: 1972, Tanzania: 1961, Zambia: 1964, Zimbabwe: 1970.). Source Marshall and Jaggers (2005)
(16)	xConstAv	Executive constraint, average value. Range: 1 (unlimited authority) - 7 (executive Parity or Subordination). Source Marshall and Jaggers (2005)

Table 14: Details on variables. LOG indicates the variables expressed in natural logarithm in our computations.

A.2 Countries

Table 15 contains the list of the countries in our sample.

Number	Country	Number	Country
1	Argentina	32	Kenya
2	Austria	33	Korea
3	Belgium	34	Luxembourg
4	Bolivia	35	Madagascar
5	Botswana	36	Malawi
6	Brazil	37	Malaysia
7	Cameroon	38	Mali
8	Canada	39	Mexico
9	Chile	40	Morocco
10	Colombia	41	Netherlands
11	Costa Rica	42	Nigeria
12	Denmark	43	Norway
13	Dom. Republic	44	Pakistan
14	Ecuador	45	Panama
15	El Salvador	46	Paraguay
16	Ethiopia	47	Peru
17	Finland	48	Philippines
18	France	49	Portugal
19	Germany	50	Senegal
20	Greece	51	Spain
21	Guatemala	52	Sri Lanka
22	Honduras	53	Tanzania
23	Hong Kong	54	Thailand
24	India	55	Tunisia
25	Indonesia	56	UK
26	Ireland	57	US
27	Israel	58	Uruguay
28	Italy	59	Venezuela
29	Ivory Coast	60	Zambia
30	Jamaica	61	Zimbabwe
31	Japan	-	-

Table 15: Country List

B The distributions of the variables

Table B reports the results of standard global tests of normality for our variables.

	Variable	AD	KS	SW
(1)	G6085	0.67	0.78	0.76
(2)	LF6085	0	0	0
(3)	GGap60	0	0	0
(4)	PE60	0	0	0.02
(5)	SE60	0	0.01	0
(6)	GovC	0.01	0	0.02
(7)	Transp	0.16	0.22	0.14
(8)	Struct	0.14	0.41	0.06
(9)	ElMach	0	0	0
(10)	NoElMa	0.01	0.08	0
(11)	FreeS	0	0.08	0
(12)	Trade	0.22	0.21	0.34
(13)	MinDep	0.24	0.47	0.21
(14)	Ores	0.5	0.46	0.58
(15)	xConstIn	0	0	0
(16)	xConstAv	0	0	0

Table 16: P-values for normality tests for all variables: AD: Anderson-Darling; KS: Kolgomorov-Smirnov; SW: Shapiro-Wilk

It can be observed that global tests reject the hypothesis of normality for most of the variables. However, if we examine the whole distribution, as suggested by Bowman and Azzalini (1997), we can observe that departures from normality appear serious for few variables and, in any case, characterize relatively small portions of the distributions. Figures 6 and 7 respectively present for each variable the distributions along with their *reference bands*,[55] and the probability plots.

[55]Reference bands are given by two standard errors above and below the estimate, indicating where the distribution should lie if the original data were normally distributed (see Bowman and Azzalini (1997), p. 41, for more details).

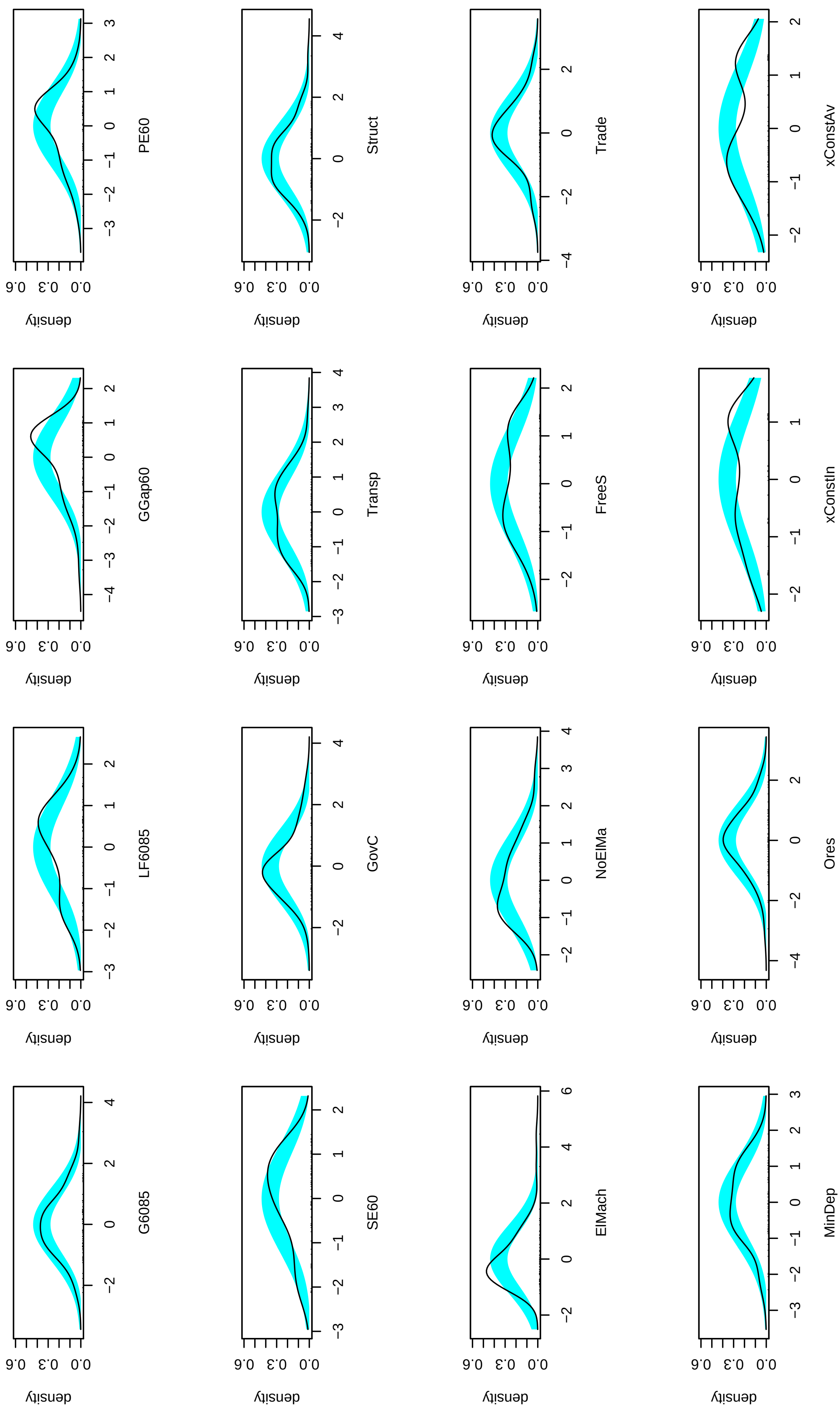

Figure 6: Density of features. Shaded area: reference band

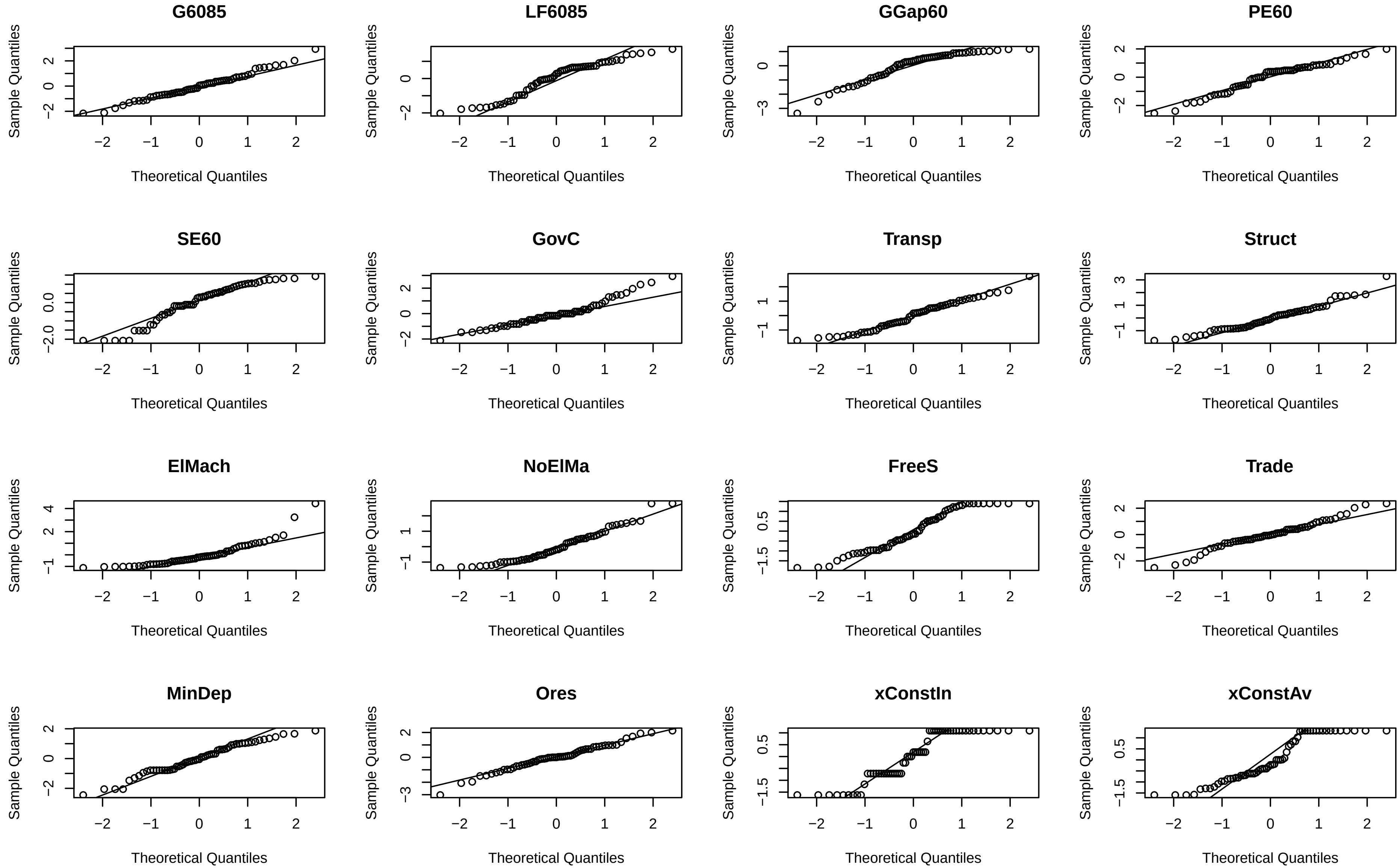

Figure 7: probability plots

In both cases we see that departures from normality appear more serious for Ggap, ElMach and for the measures of institutions, in particular XconstIn and XconstAv. As for the latter, this depends on the fact that they are based on discrete scores. Our procedure of combining the two scores of Freedom House (2007) introduces some smoothing in the scores, and is likely to determine the smaller departure from normality of FreeS. In any case, departures from normality seem to affect limited portions of the distribution, as highlighted in particular by the reference bands in Figure 6.

C Robustness Tests for the Clustering of Countries

In this section we carry out some tests to check the robustness of the clustering presented in the main text.

C.1 Robustness to variable definition

Table 17 contains a comparison between the cluster structure obtained in Ex 1 and the clusterings obtained with Ex 2, Ex 3, Ex 4 and DES. The latter, as remarked, is obtained applying the GM algorithm to the dataset originally used by Desdoigts (1999), comprising ten variables only. In addition, we also report in the last column the cluster structure obtained by Desdoigts (1999), indicated by *ALD*.

		SA					MR					
	Country	Ex 1	Ex 2	Ex 3	Ex 4	DES	Ex 1	Ex 2	Ex 3	Ex 4	DES	ALD
2	Austria	1	1	1	2	3	1	6	1	1	4	2
17	Finland	1	11	3	2	3	7	6	1	2	4	1
18	France	1	7	3	2	1	1	8	2	2	1	2
19	Germany	1	1	1	2	1	1	1	1	2	1	2
20	Greece	1	11	3	2	3	7	6	2	2	4	2
26	Ireland	1	1	1	1	3	1	6	1	1	4	2
28	Italy	1	1	1	2	1	1	1	1	2	1	2
31	Japan	1	11	3	2	3	7	6	2	2	4	1
49	Portugal	1	7	3	2	3	1	8	2	2	4	2
51	Spain	1	7	3	2	3	7	8	2	2	4	2
3	Belgium	2	1	1	1	1	3	1	1	1	1	1
12	Denmark	2	1	1	1	7	1	1	1	1	5	1
34	Luxembourg	2	1	1	1	1	3	1	1	1	1	2
41	Netherlands	2	1	1	1	1	3	1	1	1	5	1
43	Norway	2	1	1	1	7	1	1	1	1	5	1
56	UK	2	1	1	1	7	1	1	1	1	5	1
16	Ethiopia	3	2	2	4	2	2	2	9	5	2	6
36	Malawi	3	2	2	3	2	4	3	4	3	3	4
38	Mali	3	2	2	3	2	5	2	6	3	3	4
50	Senegal	3	2	2	4	2	2	2	9	5	3	4
53	Tanzania	3	2	2	3	2	5	2	6	3	3	4
21	Guatemala	4	5	4	14	12	2	7	3	8	11	6
22	Honduras	4	3	4	4	12	2	4	3	8	11	5
40	Morocco	4	3	4	4	5	2	4	3	4	2	4
55	Tunisia	4	3	4	6	5	2	4	3	4	2	6
7	Cameroon	5	6	7	6	5	4	3	4	4	2	7
29	IvoryCoast	5	6	7	3	5	4	3	4	3	2	4
32	Kenya	5	6	7	3	2	4	3	4	3	2	4
35	Madagascar	5	10	10	4	2	13	13	13	5	3	6
44	Pakistan	5	6	7	14	5	13	3	13	10	2	6
4	Bolivia	6	4	5	5	8	6	5	5	6	8	6
47	Peru	6	4	5	5	6	6	5	5	6	6	6
48	Philippines	6	4	5	5	6	6	5	5	6	6	3
13	DRepublic	7	5	8	8	4	8	7	8	9	7	5
25	Indonesia	7	5	8	8	4	8	7	8	9	7	6
37	Malaysia	7	15	8	8	4	8	15	8	9	7	6
8	Canada	8	8	9	7	9	9	9	10	7	9	1
57	US	8	8	9	7	9	9	9	10	7	9	1
6	Brazil	9	9	6	9	11	10	10	7	11	7	6
10	Colombia	9	9	13	10	4	10	10	11	10	7	5
24	India	9	9	16	9	8	10	17	17	11	8	6
39	Mexico	9	9	13	9	4	10	10	11	11	7	5
11	CostaRica	10	10	10	11	6	11	15	12	12	6	6
15	ElSalvador	10	10	10	11	6	11	13	12	12	6	5
59	Venezuela	10	15	13	11	6	11	15	11	12	6	5
33	Korea	11	16	6	6	11	12	16	7	4	12	3
46	Paraguay	11	5	6	10	4	12	7	7	10	6	5
54	Thailand	11	5	6	6	11	12	7	7	4	12	3
1	Argentina	12	12	11	9	10	14	11	14	11	10	7
9	Chile	12	12	11	9	10	14	11	14	11	10	5
14	Ecuador	12	12	11	10	10	14	11	15	10	10	6
30	Jamaica	13	13	12	13	13	15	12	18	14	13	7
42	Nigeria	13	13	12	4	12	2	12	9	8	11	5
60	Zambia	13	13	12	13	13	15	12	9	14	13	4
61	Zimbabwe	13	13	12	13	13	15	12	9	14	13	6
45	Panama	14	14	14	12	10	13	14	15	13	10	6
52	SriLanka	14	14	14	12	8	13	14	13	13	8	6
58	Uruguay	14	14	14	12	14	17	17	17	13	15	2
5	Botswana	15	17	15	15	28	16	18	16	15	14	7
23	HongKong	15	16	15	15	11	16	16	16	15	14	3
27	Israel	17	17	16	48	14	17	18	19	16	15	7

Table 17: Clusterings from Ex 1, Ex 2, Ex 3, Ex 4; SA and MR

From visual inspection of Table 17 we can notice that the cluster structure obtained with SA in Ex 1 is quite robust, in particular with respect to the clusterings obtained with Ex 2 - Ex 4, and to those obtained using MR instead of SA. Some clusters appear particularly resistant to changes in the variables and changes in the procedure to maximize the likelihood, for example: Cluster 2, containing North European countries, Cluster 3, containing Sub-Saharan countries, and Cluster 8, containing North American countries. In addition, countries in Cluster

1, belonging essentially to central-southern Europe, are split in two subgroups in the cluster structures different from those obtained performing Ex 1, with the partial exception of Ex 2. In all cases, however, these countries recombine with other OECD countries

Visual inspection, however, cannot provide an exact quantification of the degree of dissimilarity among the clusterings. For this reason, we compare the clusterings obtained with SA following some commonly used methods of comparing partitions: the methods of Rand (1971), Meilă (2007) and Zhou *et al.* (2005), respectively indicated as *Rand*, *VI* and *Mall.*

The method of Rand (1971) is based on the count of the number of pairs of objects, countries in our case, that belong to the same cluster in the two partitions of interest. It takes the value of zero if the two partitions are identical, and of one if there are no similarities, i.e.: "when one [clustering] consists of a single cluster and the other only of clusters containing single points" (Rand (1971), p. 847). The method of Meilă (2007), instead, aims at measuring the *variation of information* that obtains by moving from one clustering to another, the information contained in a clustering being related to the entropy associated with it (see Meilă (2007), pp. 878-880, for more details). This index takes the value of zero if the clusterings are identical, and the value of $log(N)$ (which equals 4.11 in our case) if the dissimilarity is maximal, as in the case indicated above for the *Rand* index.[56] The *Mall* index is obtained from an: "optimal cluster matching scheme" (Zhou *et al.* (2005), p. 1031). In particular, we consider here a special case of the procedure described in Zhou *et al.* (2005), as our exercise consists in a *hard clustering* of the countries, i.e. in a partition[57] in which no special weights are given to the clusters in comparing the partitions. This amounts to compute the "Manhattan dissimilarity", i.e. "the minimal sum of the absolute differences of M and all column permutations of M'" (Hornik (2005), p. 7), where M and M' are the membership matrices of two partitions.[58]

Tables 18 and 19 contain the results of, respectively, comparisons between the clusterings obtained applying SA (Ex 1 vs Ex 2, Ex 3, Ex 4, DES and ALD), and between the clustering obtained applying SA in Ex 1, with those obtained applying MR.

Index (range)	Ex 2	Ex 3	Ex 4	DES	ALD
Rand (0 - 1)	0.05	0.04	0.04	0.06	0.06
VI (0 - 4.11)	0.67	0.48	0.86	1.07	1.46
Mall (0 - 120)	28	16	28	44	90

Table 18: Comparison between Ex 1 and Ex 2, Ex 3, Ex 4, DES, ALD. SA

[56] Meilă (2007), p. 886, suggests the possibility to normalize the index to the interval $[0, 1]$ by dividing the values by $log(N)$, but only if the two clusterings are obtained from the same dataset, e. g. by applying two different clustering algorithms, which is not the case here.

[57] With *soft clustering* each object is assigned to a cluster with some probability.

[58] A membership matrix is a N X K^* matrix, where K^* is the number of clusters, and each row of the matrix contains zeros except for the element (i, s) which takes on the value of 1 if object i belongs to cluster s. This is the case for hard clustering. For soft clustering the rows of the membership matrix are probability distributions.

Index (range)	Ex 1	Ex 2	Ex 3	Ex 4	DES
Rand (0 - 1)	0.05	0.05	0.06	0.05	0.06
VI (0 - 4.11)	0.7	0.8	0.84	0.85	1
Mall (0 - 120)	28	32	34	30	40

Table 19: Comparison between Ex1 (SA) and Ex1, Ex2, Ex3, Ex4, DES (MR)

From Table 18 we notice that: i) the dissimilarity between the clustering from Ex 1 and those from Ex 2 - Ex 4 is very low. In particular, it is lowest in the comparison with Ex 3; ii) it is higher with respect to the clustering from DES; iii) it is much higher in a comparison with the cluster structure obtained by Desdoigts (1999). From Table 19 we also notice that the application of MR would actually make little difference.

Finally, if we compare the partitions labeled DES (obtained with both SA and MR) and ALD, we obtain, respectively for the indices *Rand*, *VI* and *Mall*, the values of: 0.06, 1.51 and 92. These values, compared to those in Tables 18 and 19 are relatively high.

C.2 Robustness to the Use of Other Clustering Algorithms

In this section we compare the clustering obtained with Ex 1 with those obtainable with other clustering algorithms. In particular, we compare our results with those resulting from the application of the procedure recently proposed by Frey and Dueck (2007) (FD henceforth), and from the application of two standard clustering methods: partitioning around Medoids (PAM), and hierarchical clustering by agglomerative nesting (AGNES) (see Kaufman and Rousseeuw (1990)).

C.2.1 Comparison with the method of Frey and Dueck (2007)

The FD procedure can be summarized as follows: it considers all data points (the countries in our sample) as nodes of a network. Then it seeks to identify *exemplars*, that is data points that can be considered as central with respect to other similar points. The procedure to identify the exemplars, a concept shared by other clustering methods (see below), is completely data-driven. The only parameter required is a "preference" parameter, i.e. a real number that indicates which point is more likely to be an exemplar. If there are no a priori assumptions or information on these probabilities, a common number can be set as the common preference for each point. Then the algorithm proceeds by passing "messages" through the network, by which each point accumulates information on candidate exemplars. The procedure stops when convergence to a certain number of exemplars is reached.

In our case, since we have no a priori information or assumptions on candidate exemplars, we set the preference parameter to a common value for all countries. Following Frey and Dueck

(2007), p. 972 we considered first of all the median value of the similarities as a preference. However, we also utilized as alternatives a value of zero and some multiples of the median (5%, 30%, ..., 160%). We computing the similarity in two ways, both based on the correlations among the objects: the first one, used in Table 20, is suggested by Kaufman and Rousseeuw (1990), p. 21; the second, used in Table 21, is a dissimilarity index which is the negative of the Euclidean distance in the features' space.

Tables 20 and 21 contain the values of the dissimilarity indices between our clustering and clusterings obtainable following Frey and Dueck (2007).

Index (range)	0	0.01	0.05	0.30	0.40	0.50	0.60	0.70	0.80	0.90	Med	1.10	1.20	1.30	**1.40**	1.50	1.60
Rand (0 - 1)	0.04	0.04	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.01	0.01	**0.01**	0.01	0.01
VI (0 - 4.11)	0.36	0.36	0.36	0.36	0.36	0.33	0.33	0.33	0.34	0.34	0.34	0.32	0.25	0.25	**0.16**	0.17	0.2
Mall (0 - 120)	18.49	18.49	18.49	18.49	18.49	16.05	16.05	16.05	16.05	16.05	16.05	14.11	9.24	9.24	**6.32**	6.81	8.27

Table 20: Comparison with clusterings obtained following Frey and Dueck (2007). Similarity given by $[1 + corr(i, j)]/2$

Index (range)	0	0.01	0.05	0.30	0.40	0.50	0.60	**0.70**	0.80	0.90	Med	1.10	1.20	1.30	1.40	1.50	1.60
Rand (0 - 1)	0.02	0.02	0.02	0.01	0.01	0.01	0.01	**0.01**	0.02	0.02	0.02	0.02	0.03	0.04	0.04	0.04	0.04
VI (0 - 4.11)	0.36	0.36	0.36	0.32	0.28	0.25	0.2	**0.21**	0.27	0.34	0.34	0.34	0.34	0.36	0.36	0.39	0.39
Mall (0 - 120)	21.89	21.89	21.89	19.46	17.51	13.62	8.76	**8.27**	10.22	11.68	12.16	12.16	16.05	17.03	17.03	17.51	17.51

Table 21: Comparison with clusterings obtained following Frey and Dueck (2007). Dissimilarity given by $-\sqrt{1 - corr(i, j)})$

Tables 20 and 21 show that the dissimilarity between the clustering obtained with the GM method and those obtained with the FD algorithm do not significantly differ. By varying the preference parameter, we are able to identify a "best" FD clustering, i.e. a cluster structure which is the least dissimilar from the Ex 1 structure. We call these clusterings, respectively, FD1 and FD2.

Table 22 contains the comparison between the Ex 1 clustering, FD1 and FD2. The latter clusterings indicate the exemplar for each identified cluster by its number.

	Country	Ex 1	FD1	FD2
2	Austria	1	28	3
17	Finland	1	28	20
18	France	1	28	19
19	Germany	1	28	19
20	Greece	1	28	20
26	Ireland	1	43	3
28	**Italy**	1	28	19
31	Japan	1	28	19
49	Portugal	1	28	19
51	Spain	1	28	20
3	Belgium	2	43	3
12	Denmark	2	43	19
34	Luxembourg	2	43	3
41	**Netherlands**	2	43	3
43	Norway	2	43	3
56	UK	2	43	19
16	Ethiopia	3	38	38
36	Malawi	3	38	38
38	**Mali**	3	38	38
50	Senegal	3	38	38
53	Tanzania	3	38	38
21	Guatemala	4	22	22
22	**Honduras**	4	22	22
40	Morocco	4	22	22
55	Tunisia	4	22	22
7	Cameroon	5	32	29
29	IvoryCoast	5	32	29
32	**Kenya**	5	32	29
35	Madagascar	5	32	15
44	Pakistan	5	32	29
4	Bolivia	6	47	47
47	**Peru**	6	47	47
48	Philippines	6	47	47
13	DRepublic	7	47	47
25	Indonesia	7	54	54
37	**Malaysia**	7	47	47
8	Canada	8	43	8
57	US	8	43	8
6	Brazil	9	39	39
10	**Colombia**	9	39	39
24	India	9	1	24
39	Mexico	9	39	39
11	**CostaRica**	10	11	15
15	ElSalvador	10	11	15
59	Venezuela	10	11	39
33	Korea	11	54	54
46	Paraguay	11	54	54
54	**Thailand**	11	54	54
1	Argentina	12	1	9
9	**Chile**	12	1	9
14	Ecuador	12	1	9
30	Jamaica	13	22	30
42	Nigeria	13	22	22
60	**Zambia**	13	38	38
61	Zimbabwe	13	22	22
45	Panama	14	52	52
52	**SriLanka**	14	52	52
58	Uruguay	14	52	52
5	Botswana	15	38	5
23	HongKong	15	23	23
27	Israel	17	38	27

Table 22: Comparison between Ex 1 and best clusterings obtained with the FD algorithm

Table 4 highlights that, besides the large similarity of the clusters identified with the different methods, there is some interesting correspondence between the exemplars and the countries that, in the GM clusters ranked the highest in terms of “significance”. These countries are indicated in bold and the high correspondence with the exemplars in FD1 is evident. However, the exemplars in FD2 often correspond, if not the the more significant countries, to countries that immediately follow.

C.2.2 Comparison with standard clustering methods

In this section we compare our results with Ex 1 with two commonly used clustering procedures: the *partitioning around medoids* method (PAM), and the *agglomerative nesting* method (AGNES), described for example in Kaufman and Rousseeuw (1990).

The PAM procedure is based on the selection of a given number of “representative objects”, *medoids*, and the remaining objects are assigned to the closest medoid. “Closeness” is defined by a distance (e. g. Euclidean). The clustering structure is obtained by minimizing the average distance of objects from the corresponding medoids. The AGNES method instead belongs to the family of hierarchical clustering methods. It starts with N clusters and, at each step, two clusters are merged until one large cluster obtains. The issue here is deciding how to merge two clusters in each step. AGNES utilizes the “unweighted pair-group average method” (Kaufman and Rousseeuw (1990), p. 203), based on the computation for two clusters of the average dissimilarity between each object of one cluster and each object of the other. The pair of clusters which displays the lowest value of the average dissimilarity is merged into one cluster, then the process re-starts.

Table 23 contain the results of the comparison of our results with PAM,[59] while Figure 8 presents the dendrogram obtained from the application of AGNES to our database.[60]

[59]We imposed the number of medoids equal to the number of clusters obtained with Ex 1, that is sixteen.

[60]A dendrogram reads in the following way: the vertical lines indicate the level of similarity of objects that are joined at each step. So, for example, Germany and Italy are initially merged, then they are joined by France etc.

	Country	Ex 1	PAM
2	Austria	1	2
17	Finland	1	2
18	France	1	2
19	Germany	1	2
20	Greece	1	2
26	Ireland	1	3
28	**Italy**	1	2
31	Japan	1	2
49	Portugal	1	2
51	Spain	1	2
3	Belgium	2	3
12	Denmark	2	3
34	Luxembourg	2	3
41	Netherlands	2	3
43	**Norway**	2	3
56	UK	2	3
16	Ethiopia	3	10
36	Malawi	3	10
38	**Mali**	3	10
50	Senegal	3	10
53	Tanzania	3	10
21	Guatemala	4	11
22	**Honduras**	4	11
40	Morocco	4	11
55	Tunisia	4	11
7	Cameroon	5	7
29	IvoryCoast	5	7
32	**Kenya**	5	7
35	Madagascar	5	7
44	Pakistan	5	7
4	Bolivia	6	4
47	**Peru**	6	4
48	Philippines	6	4
13	DRepublic	7	4
25	Indonesia	7	9
37	**Malaysia**	7	9
8	Canada	8	3
57	US	8	3
6	Brazil	9	6
10	Colombia	9	6
24	India	9	1
39	**Mexico**	9	6
11	**CostaRica**	10	8
15	ElSalvador	10	8
59	Venezuela	10	8
33	Korea	11	15
46	Paraguay	11	15
54	**Thailand**	11	15
1	**Argentina**	12	1
9	Chile	12	1
14	Ecuador	12	9
30	**Jamaica**	13	14
42	Nigeria	13	11
60	Zambia	13	10
61	Zimbabwe	13	11
45	Panama	14	16
52	**SriLanka**	14	16
58	Uruguay	14	16
5	Botswana	15	5
23	HongKong	15	12
27	Israel	17	13

Table 23: PAM, Reordered with Ex1 Gs0

Table 23 shows that the differences are not remarkable: computation of dissimilarities using, respectively, the *Rand*, *VI*, and *Mall* methods returns the values of: 0.03, 0.58, 20. In 23 we also indicate in bold the identified medoids: notice the large overlap with the representatives identified in Section C.2.1 by the application of the FD method.[61]

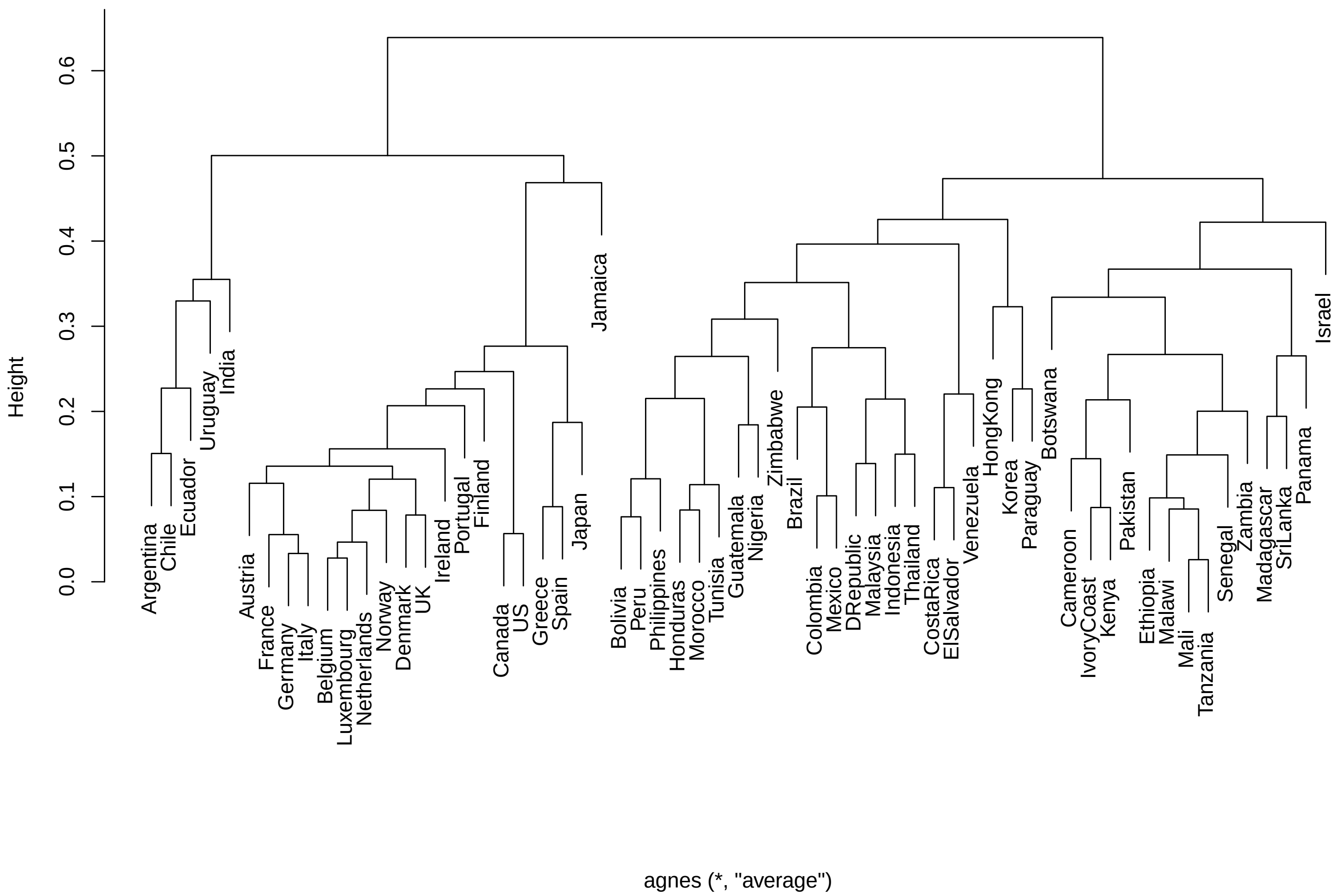

Figure 8: Dendrogram obtained by the application of the AGNES method

Figure 8 essentially confirms the patterns identified with Ex 1. With respect to OECD countries, we notice that it is confirmed that the most relevant religion for the clustering is Catholicism, casting further doubts on Desdoigts (1999)'s claims. Geography also appears relevant as, initially, two groups of geographically close countries emerge: i) Austria, France, Germany, and Italy; ii) Belgium, Luxembourg, Netherlands, Norway, Denmark and UK.[62] Then these two groups are then merged and, subsequently, they are joined by Ireland (Catholic), Portugal (Catholic), Finland (Protestant), Canada (mostly Catholic) and US (protestant),

[61]Botswana, Hong Kong and Israel are identified as medoids, as they represent isolated clusters.

[62]The first group corresponds to the most significant countries in Cluster 1 in Table 3, while the second group exactly corresponds to Cluster 2 of Table 3.

Greece (Orthodox), Spain (Catholic) and Japan (Shintoist/Buddhist).

Hence, the classification by religion certainly matters, but its primacy over OECD membership in clustering the countries is dubious (otherwise we should have observed more clustering by religion in the initial steps of the merging procedure).

D Growth Paths

In this section we present the figures corresponding to Figures 2 and 3 in Section 4.2, for Ex 2, Ex 3, Ex 4 and DES.[63]

In general the pattern of the cluster of OECD countries is always found. The second most stable Cluster, as remarked, is the one found at the lowest productivity levels. In Ex 2 it is consistent with Ex 1, while in Ex 3, Ex 4 and, especially DES, it is spread over a larger productivity range (and therefore includes other countries not from Sub-Saharan Africa).

With respect to Clusters 2 and 3, we notice that in Ex 3 and Ex 4 they do not appear. In this case we have only three clusters: a first cluster of poor countries with unstable growth rates, a second cluster with sustained growth, and a third cluster of convergence.

The most different results are found when only the ten variables of Desdoigts (1999) are considered.

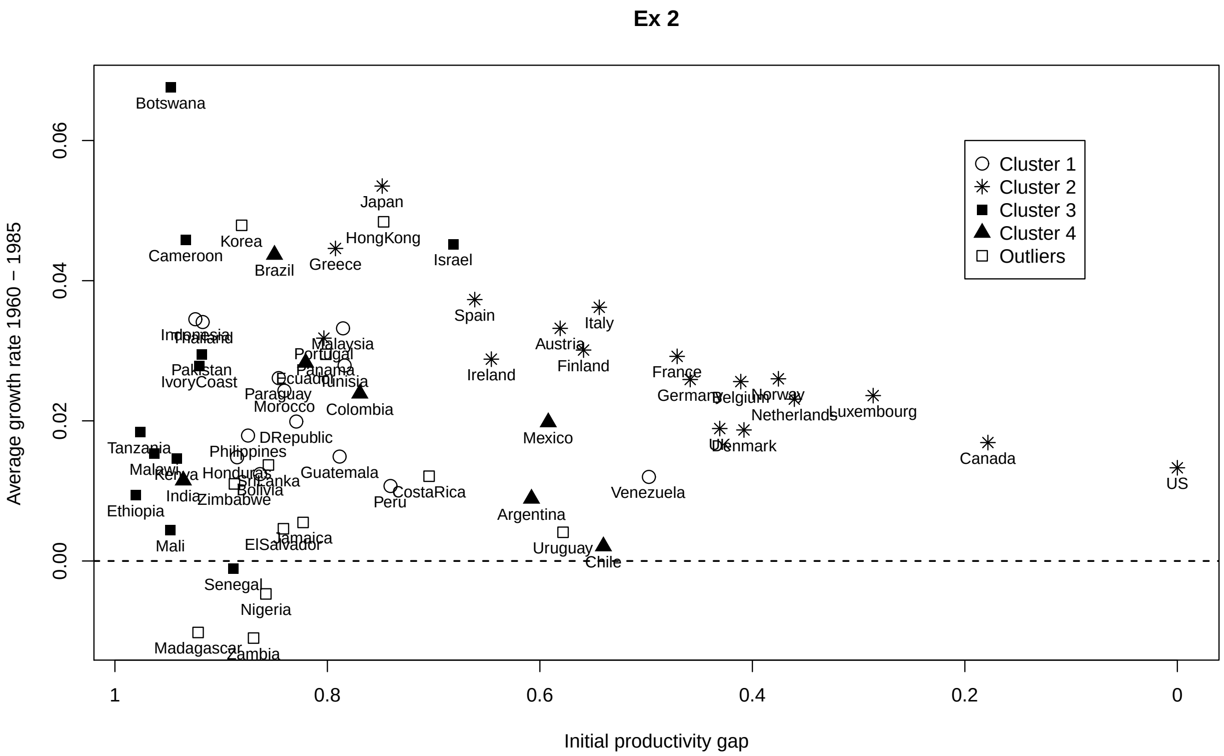

Figure 9: Relation between average growth rate and initial productivity: full sample. Ex 2

[63]Labels of growth regimes are those generated by the Fortran code.

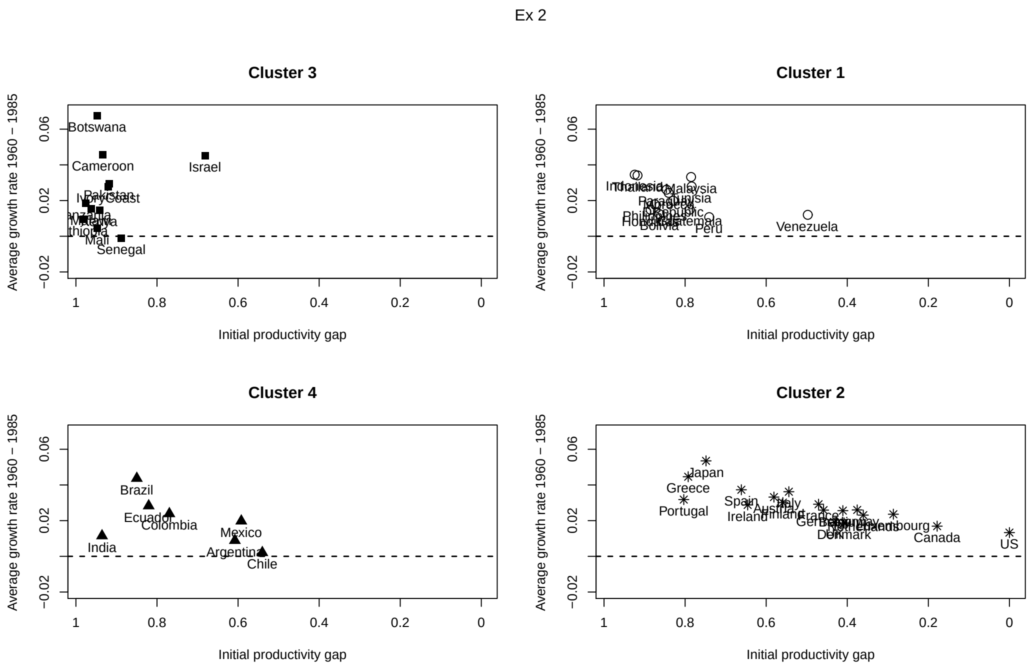

Figure 10: Relation between average growth rate and initial productivity: four clusters. Ex 2

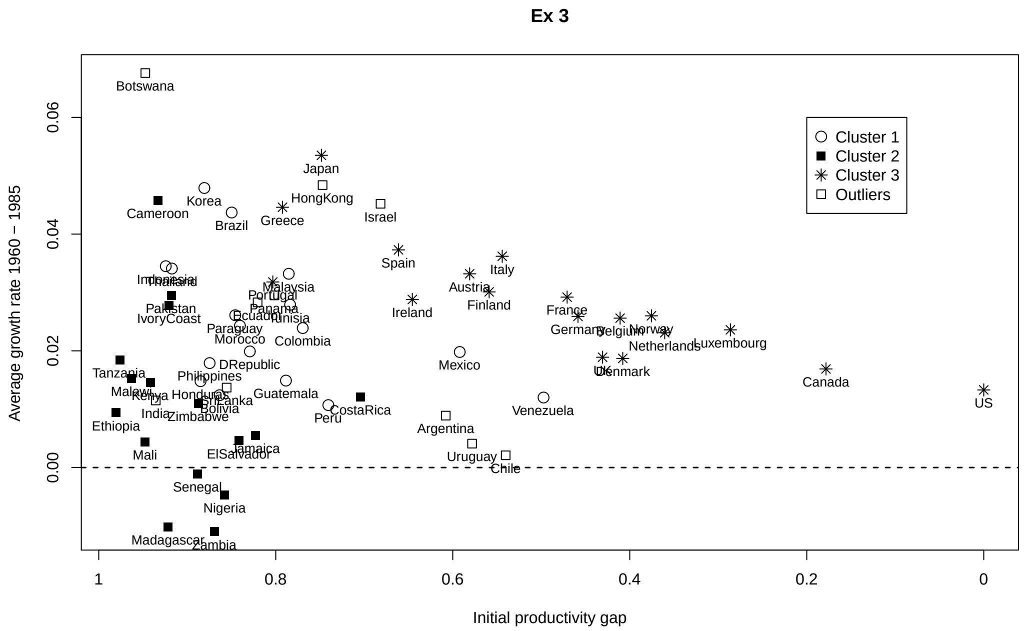

Figure 11: Relation between average growth rate and initial productivity: full sample. Ex 3

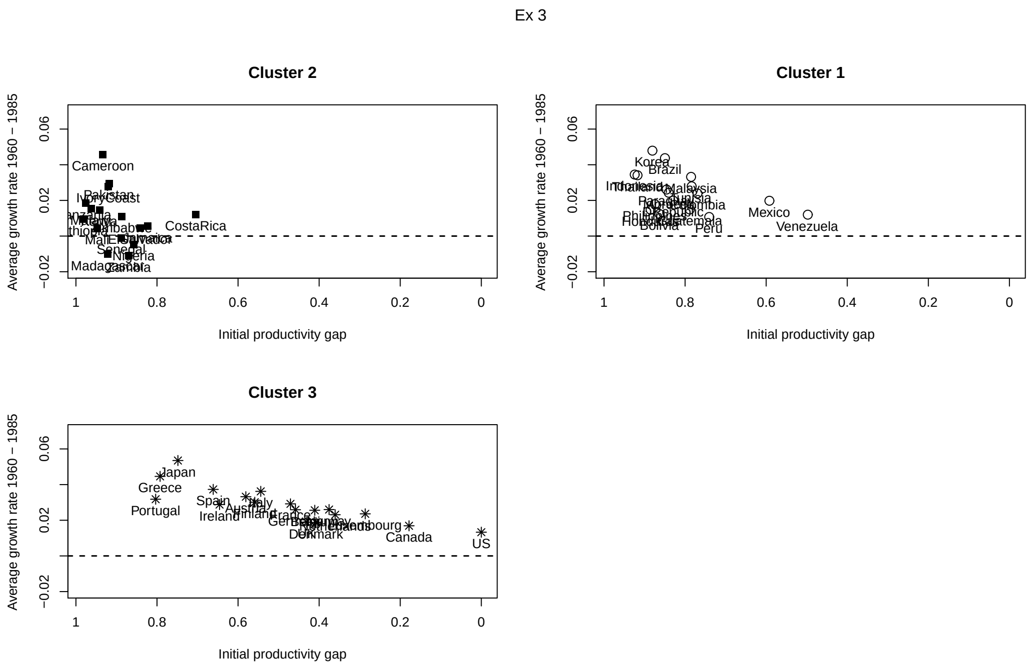

Figure 12: Relation between average growth rate and initial productivity: four clusters. Ex 3

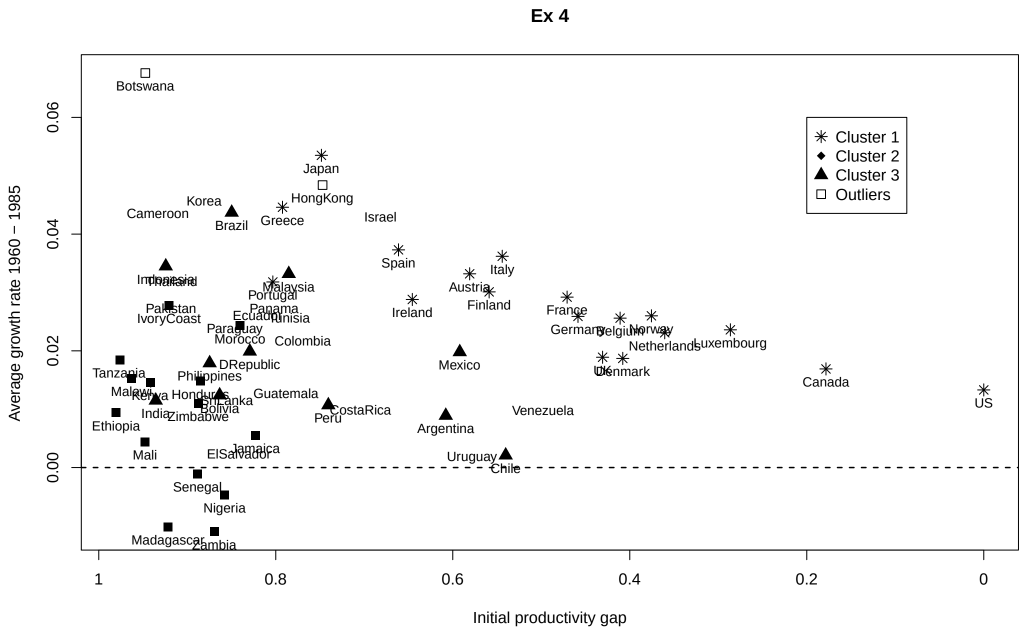

Figure 13: Relation between average growth rate and initial productivity: full sample. Ex 4

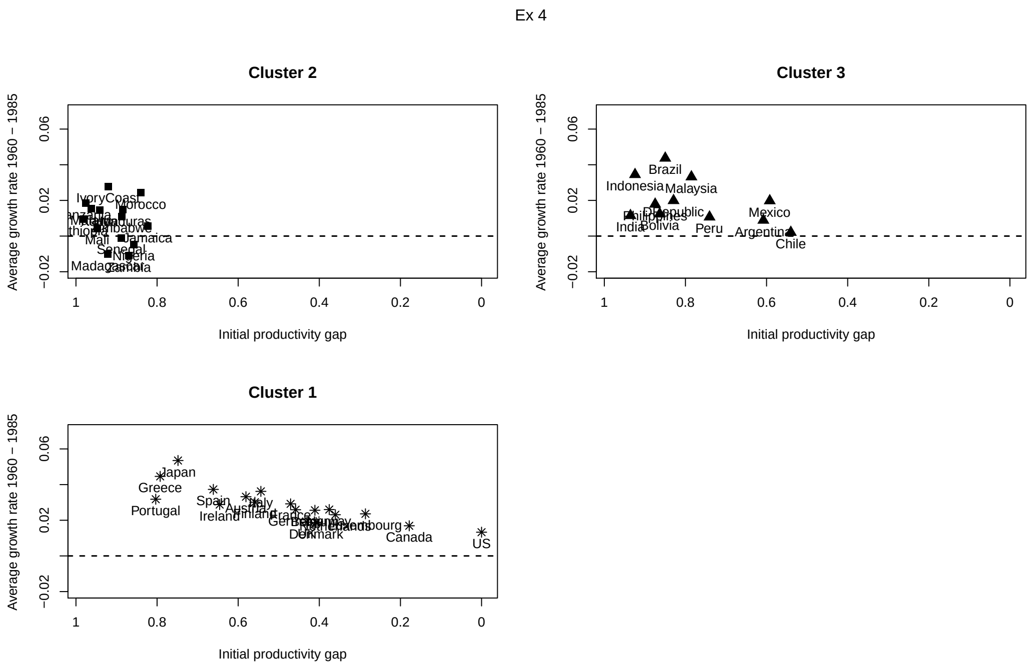

Figure 14: Relation between average growth rate and initial productivity: four clusters. Ex 4

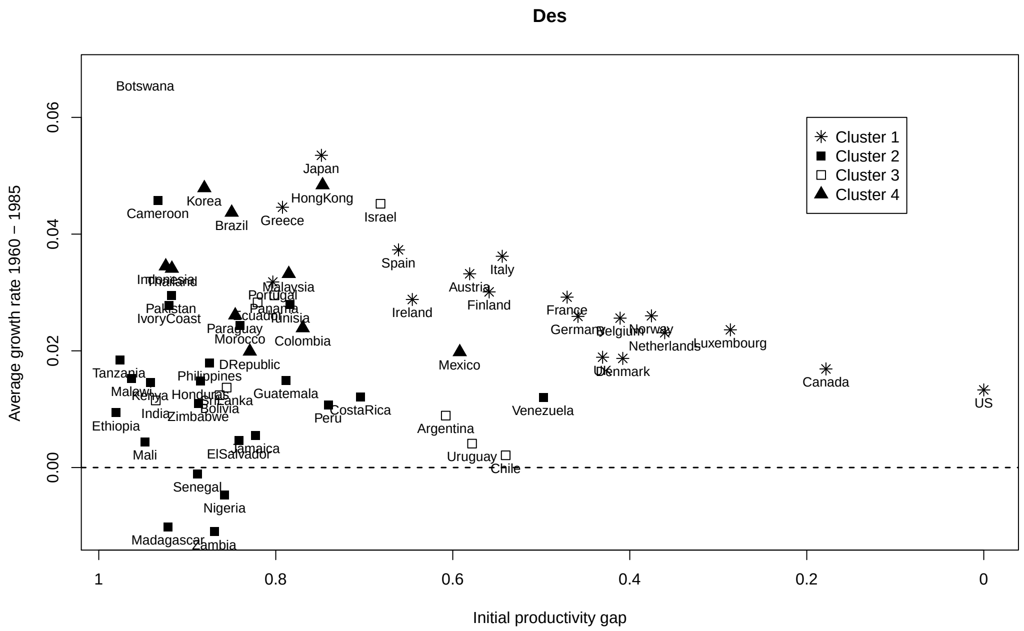

Figure 15: Relation between average growth rate and initial productivity: full sample. DES

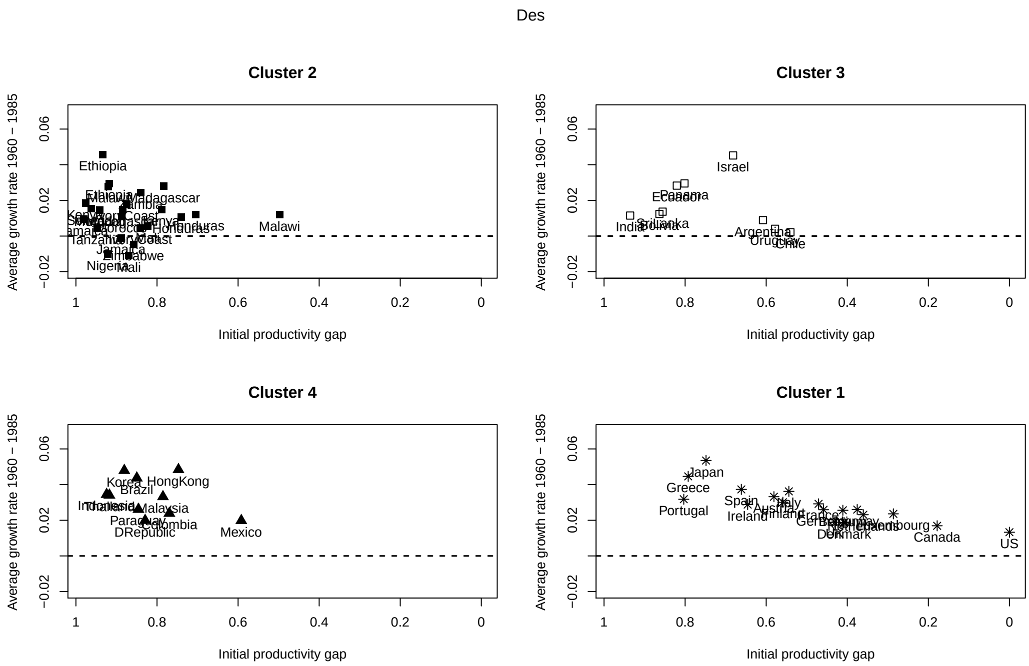

Figure 16: Relation between average growth rate and initial productivity: four clusters. DES

E Robustness Tests for the Clustering of Variables

In this section we report the results of the clustering of the variables with the clusterings obtained with Ex 2, Ex 3, Ex 4 and DES. These clusterings are similar, but not identical, to those identified with Ex 1 (see Table 4). As predictable, we find the largest correspondence to the results obtained for Ex 1 for the whole sample, and for Clusters 1 and 4, i. e. the clusters that proved more robust to the change in the definitions of the variables measuring institutions and natural resources.

E.1 All countries

We can see from Tables 9, 24, 25, 26, and 27, that the features found in the strongest clusters, i.e. Cluster All.I (-SE60, -PE60, -FreeS, GGap60) and Cluster All.II (ElMach, NoElMa, Transp, G6085), are essentially clustered together in Ex 2, Ex 3 and Ex 4 and DES.

Cluster 1, g = 0.7026		Cluster 2, g = 0.7164	
-SE60	-0.9228	ElMach	-0.6895
-PE60	-0.7970	NoElMa	-0.6231
GGap60	-0.6606	Transp	-0.4008
-Struct	-0.3927	G6085	-0.1246
-xConstIn	-0.1684		
LF6085	-0.1480		

Table 24: Clusters of features: all countries. Ex 2. Other clusters: GovC and Trade (g = 0.3276), MinDep

Cluster 1, g = 0.7432		Cluster 2, g = 0.7164	
-SE60	-0.9813	ElMach	-0.6895
-PE60	-0.8531	NoElMa	-0.6231
GGap60	-0.7210	Transp	-0.4008
-xConstAv	-0.4285	G6085	-0.1246
-Struct	-0.3135		
LF6085	-0.1432		

Table 25: Clusters of features: all countries. Ex 3. Other clusters: GovC and Trade ($g = 0.3276$), MinDep

Cluster 1, g = 0.9364		Cluster 2, g = 0.7164	
-SE60	-1.2553	ElMach	-0.6895
-PE60	-1.0141	NoElMa	-0.6231
-FreeS	-0.9584	Transp	-0.4008
GGap60	-0.9097	G6085	-0.1246

Table 26: Clusters of features: all countries. Ex 4. Other clusters: LF6085 and Struct ($g = 0.4496$), GovC and Trade ($g = 0.3276$), Ores

Cluster 1, g = 0.7717		Cluster 2, g = 0.7164	
-SE60	-0.9324	ElMach	-0.6895
-PE60	-0.9048	NoElMa	-0.6231
GGap60	-0.6468	Transp	-0.4008
-Struct	-0.3460	G6085	-0.1246
LF6085	-0.0584		

Table 27: Clusters of features: all countries. DES. Other clusters: GovC

E.2 Cluster 4

In this section we compare the clusterings of the features with the clusters that correspond to Cluster 4 in Ex 1 in Ex 2, Ex 3 and Ex 4 and DES. Many characteristics of the clusters of features in Cluster 4 are recovered: a negative relation between initial productivity, human capital and institutions; some correlation among investment components, and among some of the latter, trade and primary education.

An interesting result appears in Ex 2, where initial constraint on government measures institutional quality, and in Ex 3. In the first case, the institutional variable is not correlated to human capital and initial productivity, in the second we have evidence of the curse of natural resources, as the growth rate and natural resources are negatively related (albeit parameter g is relatively low)

Cluster 1, g = 0.9369		Cluster 2, g = 0.7813		Cluster 3, g = 0.7609	
GGap60	-1.3250	ElMach	-0.7110	NoElMa	-0.7602
-Struct	-1.1048	G6085	-0.6919	GovC	-0.6930
-SE60	-0.9089	Trade	-0.5923	xConstIn	-0.3998
-PE60	-0.7800	Transp	-0.2660	MinDep	-0.2503

Table 28: Clusters of features: Cluster 3. Ex 2. Other clusters: LF6085

Cluster 1, g = 0.9104		Cluster 2, g = 0.8920		Cluster 3, g = 0.6992		Cluster 4, g = 0.6126	
ElMach	-1.3575892	-SE60	-1.0525415	G6085	-0.28039360	GovC	-0.21153286
Transp	-1.0002055	GGap60	-0.90405989	-MinDep	-0.28039360	Trade	-0.21153286
Struct	-0.62924695	-xConstAv	-0.80883551				-0.21153286
NoElMa	-0.48875380	-PE60	-0.54100060				

Table 29: Clusters of features: Cluster 2. Ex 3. Other clusters: LF6085

Cluster 1, g = 0.923		Cluster 2, g = 0.872		Cluster 3, g = 0.968	
-FreeS	-1.3823997	Struct	-1.1968088	ElMach	-0.99806732
GGap60	-1.2510426	Transp	-0.83726692	NoElMa	-0.99806732
-SE60	-0.84323740	Trade	-0.63244450		
-Ores	-0.0809958	PE60	-0.27367461		

Table 30: Clusters of features: Cluster 2. Ex 4. Other clusters: G6085 and LF6085 ($g = 0.4310$), GovC

Cluster 1, g = 0.885		Cluster 2, g = 0.689	
ElMach	-1.2343032	GGap60	-0.76063836
Transp	-0.89559734	-SE60	-0.72963035
NoElMa	-0.56474757	-PE60	-0.61568421
Struct	-0.42586672	GovC	-0.15498209
		-LF6085	-0.05073011

Table 31: Clusters of features: Cluster 2. DES. Other clusters: G6085

E.3 Cluster 2

In this section we consider the clustering of the features in the clusters corresponding to Cluster 2 in Ex 1. However, given that with Ex 3, Ex 4, and DES this correspondence is particularly weak (see Table 4), we consider only Ex 2. The characteristics that can be recovered are: the negative correlation between initial productivity and institutional quality, and the positive correlation between the two human capital variables, which in this case belong to the same cluster with initial productivity and institutions.

Cluster 1, g = 0.6396		Cluster 2, g = 0.9419		Cluster 3, g = 0.9098		Cluster 4, g = 0.8317		Cluster 5, g = 0.6730	
-SE60	-0.5924	Transp	-0.7844	GovC	-0.6378	NoElMa	-0.4457	G6085	-0.2575
-LF6085	-0.4720	ElMach	-0.7844	MinDep	-0.6378	Trade	-0.4457	Struct	-0.2575
GGap60	-0.4233								
-PE60	-0.4011								
-xConstIn	-0.2376								

Table 32: Clusters of features: Cluster 1. Ex 2

E.4 Cluster 3

In this section we consider the clustering of the features in the clusters corresponding to Cluster 3 in Ex 1. However, given that with Ex 3, and DES this correspondence is particularly weak (see Table 4), we consider only Ex 2 and DES.

In this case we only recover the positive correlation between the growth rate and some investment components.

Cluster 1, g = 0.8521		Cluster 2, g = 0.9523		Cluster 3, g = 0.9963		Cluster 4, g = 0.5472	
-Struct	-1.0352	G6085	-1.2035	SE60	-1.8864	GovC	-0.1699
-PE60	-0.7456	NoElMa	-1.0550	-LF6085	-1.8864	MinDep	-0.1699
GGap60	-0.7189	Transp	-0.8791				
xConstIn	-0.6859						
ElMach	-0.6420						

Table 33: Clusters of features: Cluster 4. Ex 2. Other clusters: Trade

Cluster 1, g = 0.9074		Cluster 2, g = 0.7970	
G6085	-1.0235	-LF6085	-0.8076
Transp	-0.9436	GovC	-0.6191
SE60	-0.8145	-ElMach	-0.4843
NoElMa	-0.7927	GGap60	-0.4791

Table 34: Clusters of features: Cluster 4. Des. Other clusters: PE60 and -Struct ($g = 0.0657$)

E.5 Cluster 1

In this section we consider the clusterings of the features in the clusters obtained with Ex 2, Ex 3, Ex 4 and DES that correspond the Cluster 1 in Ex 1, i.e. the cluster of OECD countries.

The similarity is very high, in particular a cluster containing the growth rate and the initial productivity gap emerges very clearly, as well as the correlation between secondary education and institutional quality.

Cluster 1, g = 0.9802		Cluster 2, g = 0.9464	
G6085	-1.1787	SE60	-0.8119
GGap60	-1.1787	xConstIn	-0.8119

Table 35: Clusters of features: Cluster 2. Ex 2. Other clusters: Struct, ElMach, -GovC and NoElMa ($g = 0.3862$); MinDep, LF6085 and -Trade ($g = 0.3564$); PE60 and Transp ($g = 0.4099$)

Cluster 1, g = 0.8778		Cluster 2, g = 0.9595	
G6085	-1.1787	SE60	-0.9102
GGap60	-1.1787	xConstAv	-0.9102

Table 36: Clusters of features: Cluster 3. Ex 3. Other clusters: Struct, ElMach, -GovC and NoElMa ($g = 0.3862$); MinDep, LF6085 and -Trade ($g = 0.3564$); PE60 and Transp ($g = 0.4100$)

Cluster 1, g = 0.9802		Cluster 2, g = 0.5866		Cluster 3, g = 0.6441	
G6085	-1.1787	FreeS	-0.4748	GovC	-0.2345
GGap60	-1.1787	SE60	-0.4140	-Struct	-0.2345
		ElMach	-0.2960		
		Transp	-0.1299		

Table 37: Clusters of features: Cluster 1. Ex 4. Other Clusters: LF6085 and Ores ($g = 0.1155$), PE60 and -NoElMa ($g = 0.1147$), Trade

Cluster 1, g = 0.9802		Cluster 2, g = 0.5087		Cluster 3, g = 0.6442	
G6085	-1.1787	SE60	-0.3012	GovC	-0.2345
GGap60	-1.1787	ElMach	-0.2459	-Struct	-0.2345
		NoElMa	-0.0781		

Table 38: Clusters of features: Cluster 1. DES. Other clusters: PE60 and Transp ($g = 0.4099$), LF6085