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NUTS 2 REGIONS CLASSIFICATION: COMPARISON OF CLUSTER ANALYSIS AND DEA METHOD

KLASIFIKACE REGIONŮ NUTS 2: POROVNÁNÍ SHLUKOVÉ ANALÝZY A METODY DEA

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Annotation

The paper deals with the problem of searching the efficient frontier and group of similar units using two methods – multivariate Cluster Analysis and multicriteria Data Envelopment Analysis. The main aim of the paper is to propose the way how to choose an optimal number of groups coming to empirical analysis. Firstly it´s necessary to find the closest characteristics for a given unit according to a previously specified criterion of similarity. After fulfilment this criterion and creating optimal groups of similar units, it´s possible to evaluate level of efficiency of homogenous NUTS 2 regions within "new" EU Member States based on Regional Competitiveness Index approach; efficiency is thus seen as a mirror of competitiveness. The idea laying behind this approach is that inefficient regions can learn more easily from those, that are more similar; and closer similarity may show for the inefficient regions how to achieve the improvement with less effort.

Key words

classification, cluster, cluster analysis, DEA method, efficient frontier, NUTS 2 region, RCI

Anotace

Příspěvek se zabývá problematikou hledání efektivní hranice a skupiny podobných jednotek za pomocí dvou metod – vícerozměrné shlukové analýzy a vícekriteriální metody analýzy obalu dat. Hlavním cílem tohoto příspěvku je navrhnout způsob, jakým vybrat optimální počet skupin vstupujících do empirické analýzy. Za prvé je nutné najít nejbližší charakteristiky pro danou jednotku podle předem zadaného kritéria podobnosti. Po splnění tohoto kritéria a vytvoření optimálních skupin podobných jednotek, je možné vyhodnotit míru efektivity homogenních regionů NUTS 2 v "nových" členských státech EU na základě přístupu Indexu regionální konkurenceschopnosti; efektivita je tak tedy chápána jako zrcadlo konkurenceschopnosti. Myšlenka, která stojí za tímto přístupem, spočívá ve faktu, že neefektivní regiony se mohou mnohem snadněji učit od těch, které jsou jim podobné; a blízká podobnost může ukázat neefektivním regionům jak dosáhnout zlepšení s menším úsilím.

Klíčová slova

efektivní hranice, klasifikace, metoda DEA, NUTS 2 region, RCI, shluk, shluková analýza

JEL classification: *C10, C67, R11, R13*

Introduction

Although the European Union (EU) is one of the most developed parts of the world with high living standards, there exist huge economic, social and territorial disparities between its Member States, and especially regions. These disparities have a negative impact on the balanced development across the EU and weaken its competitiveness in the global context. Globalization, rapid technological change, an ageing population and new knowledge economies are external factors which are becoming a growing threat. But there are also some internal factors which are a big challenge for the EU, e.g. the process of enlargement, and the EU thus needs to transform its economy and society. The EU enlargement in years 2004, 2007 and 2013 is associated with increased regional disparities what a threat for European competitiveness and internal cohesion is. Heterogeneity of the EU Member States and especially regions is so high in many areas. The European integration process is thus guided by striving for two different objectives: to foster economic competitiveness and to reduce disparities (growing after EU enlargement history) (Molle, 2007). Europeôs economic challenge is to secure its position in global markets facing intense challenges from its competitors, but firstly the EU has to solve its internal problems in many areas and both in ñoldò and ñnewò EU Member States. The main aim of the paper is to recognize optimal groups of similar units for subsequent relevant efficiency analysis of homogenous NUTS 2 regions within ñnewò EU Member States based on Regional Competitiveness Index 2013 (RCI) approach.

1. Importance of understanding the efficient frontier

To find the way how to choose an optimal number of groups coming to further empirical analysis, firstly, it´s necessary to find the closest characteristics for a given unit according to a previously specified criterion of similarity. Similarity can be interpreted as closeness between the inputs and outputs of the assessed unit and the proposed targets, and this closeness can be measured by using either different distance functions or different efficiency measures. Depending on how closeness is measured, the paper solves the problem of searching the efficient frontier and group of similar units by using two methods ï multivariate Cluster Analysis (CA) and multicriteria Data Envelopment Analysis (DEA). This approach should guarantee to reach the closest projection point on the Pareto-efficient frontier. Thus, proposed way leads to the closest targets by means of a single-stage procedure, which is easier to handle than those based on algorithms aimed at identifying all the facets of the efficient frontier. Why are we applying the methods of CA and DEA in the paper? Because for fulfilment the criterion of similarity, it´s necessary to create optimal groups of units, and after that, it´ll be possible to evaluate level of efficiency of homogenous NUTS 2 regions of ñnewò EU Member States based on RCI 2013 approach. For meaningful and relevant measuring efficiency by DEA method, it´s necessary to note that DEA is a methodology for the assessment of relative efficiency of a set of homogenous decision-making units (DMUs) that use several inputs to produce several outputs. DEA models generally provide both efficiency measures for each of the assessed DMUs and information on the peers and target that have been used in the efficiency assessment in the case of inefficient DMUs. The most important mentioned point is that DMUs must be homogenous, i.e. mutually comparable in the field of inputs and outputs. How is possible to recognize that group of DMUs are in fact homogenous? Dividing the whole group of initial DMUs to smaller group of homogeneous units could be ensured just by using of CA or DEA.

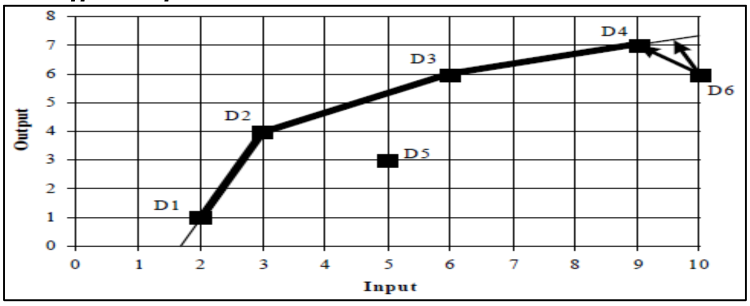
Cluster analysis represents a group of multivariate methods whose primary purpose is to cluster objects based on the characteristics they possess. CA classifies objects that are very similar to others in the cluster based on a set of selected characteristics. The resulting cluster of objects should exhibit high internal (within-cluster) homogeneity and high external (between-cluster) heterogeneity (Hair, Black, et al., 2009). Objects in a specific cluster share many characteristics, but are very dissimilar to objects not belonging to the cluster. The aim of CA is to minimize variability within clusters and maximize variability between clusters and from this point of view CA seems to be convenient as one of the methods used for creating groups of units which are relevant to efficiency analysis. There is several clustering procedure how to form the groups of objects; in the paper we used the hierarchical

CA using the dissimilarities such as distances between objects when forming the clusters. The distance is defined as Squared Euclidean distance suitable for categorical variable. After the determination of the distance measure, the clustering algorithm has to be selected. The most frequently used method is Ward's method used in the paper. The last step of CA is interpretation of the results. The most important is to select the cluster solution representing the best data sample.

DEA is multicriteria decision making method for evaluating efficiency of a homogenous group (DMUs). The aim of DEA method is to examine DMU if they are efficient of inefficient by the size and quantity of consumed resources and by the produced outputs. DEA can successfully separate DMUs into two categories which called efficient DMUs and inefficient DMUs (Cook, Seiford, 2009). Efficient DMUs have equivalent efficiency score. However, they don't have necessarily the same performance. DMU is efficient if the observed data correspond to testing whether the DMU is on the imaginary "efficient frontier". All other DMU are simply inefficient. For every inefficient DMU, DEA identifies a set of corresponding efficient units that can be utilized as benchmarks for improvement. But this improvement could be the best, we promotes the idea that inefficient DMUs can learn more easily from those, that are more similar; and closer similarity may show for the inefficient DMUs how to achieve the improvement with less effort. DEA also offers a possible way for creating similar groups. Evaluated DMUs can be divided into groups-levels according to all efficient frontiers via Context-Dependent DEA approach. By this stratification, into efficiency analysis we will enter more homogenous groups of regions, which will be evaluated separately according to closer features.

The intent of frontier estimation is to deduce empirically the production function in the form of an efficient frontier. That is, rather than knowing how to convert functionally inputs to outputs, these methods take the inputs and outputs as given, map out the best performers, and produce a relative notion of the efficiency of each. The problem with the existing methods is that they each measure efficiency in a conceptually suspect, albeit computationally effective, way. If the DMUs are plotted in their input/output space, then an efficient frontier that provides a tight envelope around all of the DMUs can be determined. The main function of this envelope is to get as close as possible to each DMU without passing by any others. A simple example of an efficient frontier is shown in Figure 1. In utilizing projections from an inefficient DMU onto the efficient frontier, it is important to understand the implications of where the projection lands. That is, it may well be that the projection lands beyond any existing DMU or any convex combination of an existing DMU. If the efficient frontier is split into two sections, one that represents either an observable or convex combination of observed input-output combinations, and another that represents extrapolations of DMUs beyond those defined in the first section, then we have what we determine as the observable portion and non-observable portion of the frontier, respectively. There are many instances in which it is not practical to have a benchmark that extends beyond the scale observed by any existing DMUs (that is, to a non-observable point), and thus, independent projections onto the observable frontier are necessary. To illustrate this, Fig. 1 duplicates the two-dimensional example from above with the observable portion of the frontier represented by a thicker line than the non-observable portion. In addition, another inefficient DMU has been added in order to illustrate that this DMUs shortest projection onto the entire frontier lands at a non-observable point. That is, the projected output for D6 is 7.2 whereas the largest observed output that of D4, is only 7. There may very well be instances in which the shortest projection onto the observable frontier, in this case directly onto D4, is the best solution. Thus, it is necessary to report both the overall efficiency score as well as the observable efficiency score. In the case of inefficient DMUs is possible to define „peer-units" as identifications efficient targets and range of improvements.

Fig. 1: The Observable efficient frontier



Source: own elaboration, 2014

For solution of CA method we used software toll IBM SPSS Statistics 22 and for DEA method software tool based on solving linear programming problems – Solver in MS Excel 2010, such as the DEA Frontier 2011 is used in the paper.

2. Theoretical background of empirical analysis

Analysis starts with building a database of indicators, which are part of RCI 2013 approach. RCI 2013 approach covers a wide range of areas having impact for territorial competitiveness including innovation, quality of institutions, infrastructure and measures of health and human capital (Annoni, Dijkstra, 2013). RCI 2013 is thus divided into pillars according to the different input and output dimensions of territorial competitiveness they describe. The terms “inputs” and “outputs” are meant to classify pillars into those which describe driving forces of competitiveness, also in terms of long-term potentiality, and those which are direct or indirect outcomes of a competitive society and economy (Annoni, Kozovska, 2010). Initial variables coming into following analysis are competitiveness scores of RCI 2013 and thus covered group of RCI 2013 input pillars and group of RCI 2013 output pillars. RCI 2013 pillars on the side of inputs are Institutions, Infrastructure, Health, Higher Education and Lifelong Learning, and Technological Readiness. RCI 2013 pillars on the side of outputs present Labour Market Efficiency, Market Size, Business Sophistication, and Innovation. RCI 2013 scores for DMUs are adjusted to positive values through Factor analysis and are shown in Tab. 3. In Tab. 1, the main descriptive statistics of initial dataset (input and output pillars) are presented across all DMUs.

Tab. 1: Descriptive statistics of initial dataset

RCI 2013 pillars	N	Range	MIN	MAX	Sum	Mean		Std. Deviation	Variance
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic
I_Institutions	57	3.120	1.210	4.330	173.400	3.04211	.088500	.668158	.446
I_Infrastructure	57	1.230	2.750	3.980	177.710	3.11772	.040042	.302313	.091
I_Health	57	3.15	1.36	4.51	155.38	2.7260	.08933	.67446	.455
I_HigherEducation LifelongLearning	57	2.55	2.14	4.69	187.55	3.2904	.07921	.59802	.358
I_Technological Readiness	57	2.58	1.85	4.43	180.82	3.1723	.08723	.65853	.434
O_LaborMarket Efficiency	57	1.55	2.96	4.51	206.70	3.6263	.05461	.41229	.170
O_MarketSize	57	1.66	2.43	4.09	171.92	3.0161	.05322	.40184	.161
O_Business Sophistication	57	3.07	2.16	5.23	172.48	3.0260	.09567	.72233	.522
O_Innovation	57	2.52	2.51	5.03	187.60	3.2912	.07236	.54629	.298
Valid N (listwise)	57	/	/	/	/	/	/	/	/

Source: own calculation and elaboration, 2014

Empirical analysis is applied to regional (NUTS 2) level within „new“ EU Member States, i.e. 13 countries entered to the EU in years 2004, 2007 and 2013. EU13 countries cover 57 NUTS 2 regions – Bulgaria 6 (BG), Cyprus 1 (CY), Czech Republic 7 (CZ)[6], Estonia 1 (EE), Croatia 2 (CR), Hungary 7 (HU), Lithuania 1 (LT), Latvia 1 (LV), Malta 1 (MT), Poland 16 (PL), Romania 8 (RO), Slovenia 2

6 The initial number of Czech NUTS 2 regions is 8; but in RCI 2013 approach, capital region CZ01 Prague is merged with its neighbouring region CZ02 Central Bohemia.

(SI) and Slovakia 4 (SK). The group of EU13 countries was chosen for empirical analysis because after accession to the EU, these countries has focused attention with regard to their functioning in “EU club of developed countries” in comparison with “old” EU Member States, i.e. EU15 countries as previous research (Melecký, 2013) mentioned. “New” EU Member States have to align their regulatory systems (legislation and related enforcement) with the internal Market acquis in order to be able to fully participate in the Single internal market and thus to be a full and competitive member this club. They must also have administrative capacity to implement the acquis. But accession to the EU is neither a necessary nor a sufficient condition for economic growth. The combined effects of market access and economic liberalization, not EU membership, optimize economic growth. From this point of view, the group of EU13 countries is a homogenous unit of competitive countries, resp. regions able to compete in comparison with EU15 countries and their regions? Does all NUTS 2 regions within EU13 countries have the same conditions for success of the Single internal market?

3. Application of DEA for efficiency evaluation of EU13 NUTS 2 regions

In the initial phase of empirical analysis, CA was applied for finding group of similar units, based on the value of competitiveness scores of RCI 2013 for each NUTS 2 region. The object is sorted into clusters, so that the degree of association is strong between members of the same cluster and weak between members of different clusters. To determine the optimum solution, in the paper is used the most common approach – method of hierarchical cluster analysis and the clustering algorithm is Ward’s method applying Squared Euclidean Distance as the distance or similarity measure. It helps to obtain the optimum number of clusters we should work with. On the basis of the Ward Linkage – Agglomeration schedule, the part “Coefficients” helped us to decide how many clusters are optimal for representation of the data. The cluster formation should be stop when the increase in Coefficients is large. In this case, the best interpretation of data ensures six-cluster solution in the case of RCI 2013. In following Tab. 2, it is possible to seen all obtain six clusters and membership of all evaluated NUTS 2 regions within EU13 countries in relevant cluster; the total number of NUTS 2 region belonging to each cluster is also marked in Tab. 2. According to membership of NUTS 2 regions, with respect to national jurisdiction of each region, it is possible to say that the clusters seem to be created by homogenous regions. Cluster I presents predominantly Czech NUTS 2 regions, but also by one small region from Slovenia, Estonia and Malta. Cluster II is created by some NUTS 2 regions within Visegrad Four (V4) countries, thus CZ, HU, PL, SK, and then one SI region. Croatian NUTS 2 regions together with one small region from Bulgaria and Romania belong to Cluster III. Cluster IV is represented predominantly by Hungarian NUTS 2 regions, and by one small region from Latvia and Lithuania. Cluster V is the largest cluster relative to the number of regions – 21 of all 57 regions belong to this group. Cluster V is created by V4 regions, i.e. Polish regions are the most contained, then Slovak, Hungarian and one Czech region. Finally, the second largest group of 12 regions, is Cluster VI; this cluster is presented only by Romanian and Bulgarian NUTS 2 region. Graphical representation of CA is Dendogram showing the boundaries of each cluster groups (see Appendix 1).

Tab. 2: Classification by CA – Obtain clusters of EU 13 NUTS 2 regions

Category of clusters						
No. 1	No. 2	No. 3	No. 4	No. 5		No. 6
CZ03	HU10	HR03	HU32	PL31	PL62	RO21
CZ05	PL12	HR04	HU33	PL34	HU21	RO42
CZ06	CZ00	BG41	HU23	PL32	HU22	RO11
CZ07	SI02	RO32	HU31	PL33	PL11	BG31
CZ08	SK01		LT00	PL42	PL51	RO22
CY00			LV00	PL43	PL21	BG34
SI01				PL41	PL63	BG32
EE00				PL61	CZ04	BG42
MT00				PL52	SK02	RO12
				SK03	PL22	RO41
				SK04		RO31
						BG33
9 NUTS 2 regions	**5 NUTS 2 regions**	**4 NUTS 2 regions**	**6 NUTS 2 regions**	**21 NUTS 2 regions**		**12 NUTS 2 regions**

Source: own calculation and elaboration, 2014

In Context-Dependent DEA method, we used a basic approach in the form of constant returns to scale (CRS) function for obtain levels generating all the efficient frontiers (see Tab. 3). With respect to obtained results, it´s possible to say that optimal solution is presented by three groups/levels of units. The object is sorted into homogenous groups of DMUs (regions) based on the size and quantity of consumed resources and by the produced outputs. Via Obtain Levels function, a continuous calculation in Context-Dependent DEA method, initial number of 57 NUTS 2 regions was divided in three groups – 1st group is created by 20 regions (predominantly by Bulgarian, Romanian and Hungarian regions; to a lesser content by one region from Cyprus, Estonia, Croatia, Malta, Poland and Slovenia); 2nd group is presented by 25 regions (predominantly by NUTS 2 regions within V4; then by one region from Bulgaria, Croatia, Latvia, Lithuania, Romania and Slovenia); 3rd group is represented by 12 regions (predominantly by Czech and Polish regions; then by one region from Bulgaria, Hungary and Slovakia).

Tab. 3: Classification by DEA CRS model – Obtain efficiency levels of EU 13 NUTS 2 regions

No.	DMU	I^1	I^2	I^3	I^4	I^5	O^1	O^2	O^3	O^4
Level 1 (CRS model) – No. of DMU 20										
1	**BG31**	1.65	2.80	2.16	2.14	2.04	2.96	2.45	2.67	2.63
3	**BG33**	2.89	2.85	1.90	2.88	2.02	2.97	2.45	3.10	2.88
4	**BG34**	1.95	2.81	1.42	2.59	2.11	3.24	2.43	2.64	2.54
5	**BG41**	2.18	3.03	2.87	3.40	2.62	4.10	2.84	4.66	3.69
7	**CY00**	3.91	2.99	4.42	3.71	3.34	4.35	3.13	3.94	3.69
15	**EE00**	3.88	2.79	3.16	3.98	3.94	3.70	2.46	3.64	4.20
17	**HR04**	2.21	3.07	2.91	2.89	3.09	3.29	3.22	3.79	3.24
18	**HU10**	3.05	3.61	2.61	3.78	3.81	3.95	3.59	4.72	4.40
21	**HU23**	3.65	2.85	1.86	3.30	3.45	3.38	2.74	2.95	3.60
23	**HU32**	3.59	3.00	1.36	3.13	3.31	3.30	2.86	2.71	3.12
27	**MT00**	4.33	2.84	4.51	2.53	4.43	3.60	2.68	4.01	3.67
31	**PL22**	2.96	3.46	2.91	3.80	3.21	3.59	3.78	3.06	3.17
44	**RO11**	2.81	2.80	2.10	2.43	2.12	4.07	2.59	2.39	3.03
46	**RO21**	1.97	2.79	2.16	2.42	1.85	3.94	2.55	2.35	2.59
47	**RO22**	2.03	2.78	1.93	2.29	1.99	3.14	2.58	2.40	2.51
48	**RO31**	2.21	3.10	2.00	2.42	2.13	3.31	2.95	2.16	2.58
49	**RO32**	1.21	3.39	2.92	4.08	2.74	4.46	3.79	4.13	4.65
50	**RO41**	2.44	2.75	2.33	2.35	2.07	3.44	2.61	2.18	2.90
51	**RO42**	1.83	2.87	1.93	2.62	2.18	3.84	2.57	2.41	3.26
53	**SI02**	3.80	3.33	3.71	4.64	3.64	4.45	3.48	4.53	4.43
Average values		**2,73**	**3.00**	**2.56**	**3.07**	**2.80**	**3.65**	**2.89**	**3.22**	**3.34**
Level 2 (CRS model) – No. of DMU 25										
2	**BG32**	1.91	2.79	2.24	2.92	2.23	3.07	2.58	2.60	2.82
13	**CZ07**	3.57	3.20	3.44	3.55	3.82	3.85	3.33	2.71	3.25
14	**CZ08**	3.67	3.26	3.38	3.85	3.97	3.56	3.55	2.72	2.92
16	**HR03**	1.95	2.90	2.89	2.88	3.22	3.36	2.74	3.74	3.05
19	**HU21**	3.65	3.45	2.07	3.54	3.61	3.72	3.24	2.74	3.38
22	**HU31**	3.59	3.10	1.84	3.31	3.40	3.18	3.04	2.51	3.55
24	**HU33**	3.59	3.07	1.78	3.02	3.42	3.67	2.84	2.75	3.24
25	**LT00**	3.10	2.88	2.09	3.52	3.63	3.39	2.69	2.89	3.45
26	**LV00**	3.17	2.94	2.19	3.34	3.11	3.24	2.45	3.53	3.22
28	**PL11**	3.18	3.21	2.57	3.24	3.24	3.82	3.27	2.88	3.16
29	**PL12**	3.02	3.46	2.84	4.01	3.24	4.23	3.49	4.16	4.00
30	**PL21**	3.12	3.28	3.21	3.41	3.21	3.69	3.38	2.84	3.70
32	**PL31**	3.16	2.85	2.86	3.42	3.09	3.72	2.80	2.46	3.14
34	**PL33**	3.17	2.95	2.70	3.40	3.09	3.25	3.10	2.24	2.71
35	**PL34**	3.06	2.76	2.99	3.22	3.09	3.77	2.66	2.45	2.91
36	**PL41**	2.96	3.14	2.82	2.98	3.30	3.48	3.14	2.53	3.04
38	**PL43**	3.05	3.22	2.55	2.94	3.30	3.77	2.93	2.62	3.01
39	**PL51**	2.90	3.19	2.64	3.45	3.32	3.81	3.23	3.04	3.22
42	**PL62**	3.28	2.84	2.70	2.75	3.20	3.32	2.69	2.62	2.89
43	**PL63**	3.21	3.03	2.97	3.37	3.20	3.78	2.96	3.03	3.42
45	**RO12**	2.51	2.85	2.20	2.57	2.07	3.18	2.62	2.45	2.67
52	**SI01**	3.80	3.22	3.64	4.22	3.64	4.07	3.23	3.49	3.51
54	**SK01**	3.44	3.98	3.52	4.69	3.79	4.51	4.09	5.23	5.03
56	**SK03**	3.26	2.97	2.87	3.19	3.61	3.16	3.16	2.86	3.03
57	**SK04**	3.26	2.92	2.66	2.93	3.52	2.97	2.94	2.97	2.93
Average values		**3.14**	**3.10**	**2.71**	**3.35**	**3.29**	**3.58**	**3.05**	**2.96**	**3.25**

No.	DMU	I^1	I^2	I^3	I^4	I^5	O^1	O^2	O^3	O^4
Level 3 (CRS model) – No. of DMU 12										
6	**BG42**	2.84	2.91	2.36	2.63	2.19	3.10	2.52	2.49	2.64
8	**CZ00**	3.49	3.82	3.72	4.63	4.09	4.47	3.74	4.39	4.51
9	**CZ03**	3.92	3.51	3.33	3.89	3.92	4.10	3.18	2.77	3.39
10	**CZ04**	3.13	3.77	2.9	3.84	3.87	3.47	3.48	2.72	3.22
11	**CZ05**	3.90	3.43	3.59	3.95	4.06	3.98	3.33	2.70	3.43
12	**CZ06**	3.59	3.54	3.78	3.59	3.99	3.85	3.30	3.21	3.58
20	**HU22**	3.65	3.53	2.35	3.61	3.60	3.97	3.08	2.75	3.09
33	**PL32**	3.12	2.89	3.2	3.22	3.09	3.31	2.85	2.22	3.19
37	**PL42**	3.11	3.16	2.67	3.12	3.30	3.56	2.86	2.95	3.09
40	**PL52**	3.32	3.25	3.02	3.27	3.32	3.56	3.27	2.56	3.06
41	**PL61**	3.07	3.01	2.65	3.19	3.20	3.24	3.03	2.59	3.10
55	**SK02**	3.13	3.52	2.98	3.51	3.78	3.44	3.38	2.63	3.27
Average values		**3.36**	**3.36**	**3.05**	**3.54**	**3.53**	**3.67**	**3.17**	**2.83**	**3.30**

I^1 Institutions, I^2 Infrastructure, I^3 Health, I^4 Higher Education and Lifelong Learning, I^5 Technological ReadinessO^1 Labour Market Efficiency, O^2 Market Size, O^3 Business Sophistication, O^4 Innovation

Source: own calculation and elaboration, 2014

Conclusion

Measurement and evaluation of efficiency is an important issue for at least two reasons. One is that in a group of units where only limited number of candidates can be selected, the efficiency of each must be evaluated in a fair and consistent manner. The other is that as time progresses, better efficiency is expected. Hence, the units with declining efficiency must be identified in order to make the necessary improvements (Greenaway, Görg, Kneller, 2008). Nowadays, for many economic entities (also for international organizations and territories, thus countries and regions) is the focus in increasing efficiency the most important task. The flagship initiative for an economic efficient Europe under the Europe 2020 strategy supports the shift towards a resource-efficient economy to achieve sustainable growth. Continuing our current patterns of resource use and output produce is not an option. Increasing economic efficiency is key to securing growth and jobs for Europe (Staníčková, 2013). It will bring major economic opportunities, improve productivity, drive down costs and boost competitiveness. But within the whole EU, there are two groups of countries – “old” and “new” Member States having different initial, not only economic, conditions for future development. From this point of view, it´s firstly necessary to recognize specific characteristics of both groups, their advantages and disadvantages, for more efficient cooperation. The purpose of this paper was recognize how to determine the appropriate group exhibiting similar features for subsequent efficiency evaluation.

Which of two used approaches (CA and DEA) in the formation of homogenous groups, is more suitable for subsequent efficiency analysis? With respect to characteristic of DEA method and one the most important requirements on the relation between the number of DMUs on the one side and the number of inputs and outputs on the other side; then with respect to classification method and expression similarity, DEA approach based on function of Obtain Levels seems to be more convenient way how to choose an optimal number of groups covering all evaluated regions coming into further efficiency analysis. Because obtained results by DEA approach show that targets are the coordinates of the efficient projection point on the frontier and thus represents levels of operation of inputs and outputs which would make the corresponding inefficient DMU, thus NUTS 2 region perform efficiently – but this improvement will be possible to propose based on subsequent efficiency analysis by DEA method. Efficiency evaluation of NUTS 2 regions within EU13 countries based on above classified 3 groups/levels is following orientation of further empirical research. Targets can thus play an important role in practice since they may indicate keys for the inefficient regions to improve their performance.

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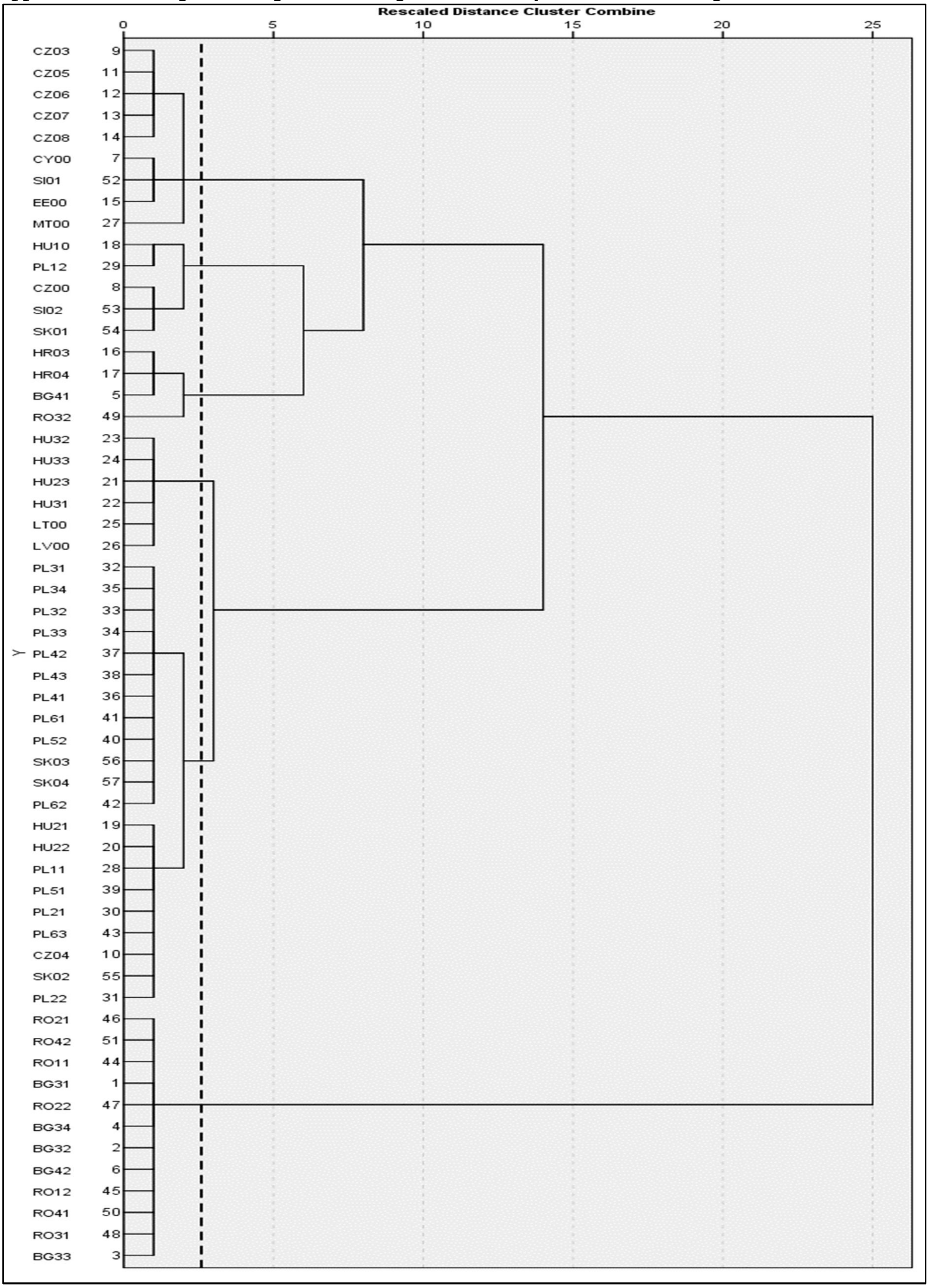
Appendix 1: Dendogram using Ward linkage – Clusters of EU 13 NUTS 2 regions



Source: own calculation and elaboration, 2014