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Regional effectiveness of innovation – leaders and followers of the EU NUTS 0 and NUTS 2 regions

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Abstract

Innovation constitutes an important factor for growth in all EU countries. Regions of the EU play a principle role in shaping new innovation trajectories and in bringing out the hidden potential for national growth. However, it is not only the level of innovation that diversifies regions, but also the innovative potential and the level of its realization. Therefore, the aim of this paper is to assess the realization of innovative potential, defined as effectiveness, in EU NUTS 0 and, if possible, NUTS 2 regions. To accomplish this goal a relative effectiveness method in used. The DEA (Data Envelopment Analysis) makes it possible to analyse the relative technical effectiveness based on regional inputs and outputs, without incorporating the legal and technological specifications of innovations, thus treating it like a production process. The inputs of the process are employment in technology and knowledge-intensive sectors and R&D expenditure, while the outputs include the number of patents and GDP. All variables are standardized by the size of the economically active population. DEA results divide regions in to two groups – **effective**, being the leaders; and **ineffective**, or followers. The DEA approach was combined and extended by ESDA (Exploratory Spatial Data Analysis) in order to pinpoint spatial patterns of innovation efficiency across NUTS 2 regions. Defining the best practices and implementing the learning-from-the-best policy is important in the process of regional development and specialization.

Key words: regional innovation, effectiveness, DEA (data envelopment analysis), regional development, spatial autocorrelation, ESDA (exploratory spatial data analysis)

JEL: C44, C46, C38, O31,O11

1. Introduction

According to the OECD, "An innovation is the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organisational method in business practices, workplace organisation or external relations. (OECD and Eurostat, Guidelines for collecting and interpreting innovation data, 2005). In this sense innovation thus constitutes a foundation for creating new enterprises, helps in job creation and, as a result, is a key factor in economic growth. For years now, the relationship between innovation and economic development, as well as productivity, has been widely acknowledged. Innovation reveals its usefulness in addressing selected social and global challenges, such as demographic changes, threats of epidemics, and even climate change. Efficiency, flexibility and strength are the main features that characterize an innovative economy. Therefore strengthening innovation is a key challenge for all EU countries and regions on their path to prosperity and, as a result, a better life.

Today, the great part of economic growth is still due to the replication of existing technologies through investment and expansion of the labour force. However while innovation still contributes only slightly to economic growth, this input is vital to attain a better standard of living in the EU. Therefore, recognition of the innovation indicators is key for benchmarking national performance as well as for comparison of local innovation performance at the regional level and its influence on economic development.

In light of the above, the aim of this paper is to assess the realization of innovative potential, measured as effectiveness or efficiency in European states (NUTS 0) and provinces (EU NUTS 2) using DEA (Data Envelopment Analysis). The DEA approach treats regions (countries and provinces) as "factories of innovation", where financial resources and human capital is transformed into patents and, indirectly, to economic development, i.e. GDP. Results of the analysis make it possible to identify the leaders, who realize their full innovative potential, and followers – regions that underachieve.

Innovations strongly depend on creativity, which cannot be measured in macro-scale, hence in order to introduce the approximation of it to the research, the DEA model with variable returns (or economies) of scale is incorporated. This makes it possible to assess the reaction of innovation outputs to a marginal change of inputs. In order to analyse the regional effectiveness of innovation, the DEA approach on efficiency was combined with spatial statistical tools for autocorrelation. This makes it possible to highlight clusters of regions (NUTS 2) with similar levels of innovation efficiency.

In Section 2 we briefly set out the methods of Data Envelopment Analysis, together with its aims and assumptions. Section 3 presents input and output variables with data description. Section 4 gives detailed empirical results for 28 EU countries in 2000-2014 and for EU NUTS 2 in 2012. Furthermore, the spatial pattern of innovation efficiency is examined using ESDA (Exploratory Spatial Data Analysis). Spatial autocorrelation of the efficiency across NUTS 2 regions makes it possible to distinguish clustered innovation efficiency, i.e. hot- and cold-spots. The major implications of the results are presented in Section 5, which additionally offers a summary and some closing remarks.

2. Methodology

Data Envelopment Analysis (DEA), introduced by Charnes, Cooper, and Rhodes in 1978, is based on the idea that the process of production, literal or figurative, performed by numerous objects (Decision Making Units – or DMU(s)) has a frontier or border of maximal effectiveness. Some DMUs fully realize their capabilities, transforming their available inputs (resources) into achievable outputs (results, effects). The efficiency or effectiveness frontier is stretched across these effective DMUs and the linear combination of their coordinates in a multidimensional space ($\boldsymbol{R}^{S+M}$, where S is the number of outputs, M is the number of inputs). All inefficient objects are below the frontier and aspire to achieve it, as they do not utilize their full production potential. The DEA approach is based on effectiveness, defined as the relationship of synthetic output (calculated as a weighted sum of results) to a synthetic input (as a weighted sum of resources). This effectiveness θ is limited to a [0,1] interval, where 1 means 100% effectiveness and $(1-\theta)\cdot 100\%$ is the amount of inefficiency. (Charnes, Cooper, Rhodes 1978, pp. 430-440; Gospodarowicz 2000, pp. 240-246)

The effectiveness of *k-th* (k=1, …,N) DMU (Decision Making Unit) with S outputs and M inputs can be presented as follows (Gospodarowicz 2002, pp.57-70):

$$\theta_k = \frac{\sum_{r=1}^{S} \mu_{rk} y_{rk}}{\sum_{i=1}^{M} \nu_{ik} x_{ik}}, \tag{1}$$

y_{rk}- *r-th* output of *k-th* DMU, r=1,…,S, x_{ik}- *i-th* input of *k-th* DMU, i=1,…,M,μ_{rk} - weight for *r-th* output of *k-th* DMU, ν_{ik} - weight for *i-th* input of the *k-th* DMU.

Basically, DEA maximizes effectiveness (1) for each DMU with respect to $\boldsymbol{\mu}$ and $\boldsymbol{\nu}$ parameters.This optimization is performed under the restriction that with the parameters used for any DMU j(j=1,…,N) (2) effectiveness is bound to [0, 1], as follows:

$$\frac{\sum_{r=1}^{S} \mu_{rk} y_{rj}}{\sum_{i=1}^{M} \nu_{ik} x_{ij}} \leq 1, \tag{2}$$

as well as non-negative values of the weights ($\mu_{rk} \geq 0, \nu_{ik} \geq 0$). Additionally, let all x_{ik} and y_{rk}, for $k \leq N$, $r \leq S$, $i \leq M$,be nonnegative ($y_{rk} \geq 0$, $x_{ik} \geq 0$). Let us also assume the existence of at least one input and one output with non-zero value ($\forall_{1 \leq k \leq N}(\exists_{1 \leq r \leq S} y_{rk} > 0 \wedge \exists_{1 \leq i \leq M} x_{ik} > 0)$).

In this analysis a DEA BCC output-oriented model is used. (Charnes, Cooper, Golany, Seinford, 1997:31-36; Gospodarowicz, 2000:36-39; Toloo, Nalchigar, 2009: 598-599). In a linearized form this model can be presented in primal form as:

$$\begin{gathered}
\max_{\boldsymbol{\theta},\boldsymbol{\lambda},\mathbf{s}^+,\mathbf{s}^-} (\boldsymbol{\theta} + \varepsilon \mathbf{J} \cdot \mathbf{s}^+ - \varepsilon \mathbf{J} \cdot \mathbf{s}^-) \\
\theta \cdot \mathbf{y}_k - \mathbf{Y} \cdot \boldsymbol{\lambda} + \mathbf{s}^+ = \mathbf{0} \\
\mathbf{X} \cdot \boldsymbol{\lambda} - \mathbf{s}^- = -\mathbf{x}_k \\
\mathbf{J}\boldsymbol{\lambda} = 1 \\
\boldsymbol{\lambda}, \mathbf{s}^+, \mathbf{s}^- \geq \mathbf{0}
\end{gathered} \tag{3}$$

or in a dual form (which is frequently the one being solved):

$$\begin{gathered}
\min_{\mathbf{v},v_k} (\mathbf{v}^T \cdot \mathbf{x}_k + v_k) \\
\boldsymbol{\mu}^{\mathrm{T}} \cdot \mathbf{y}_k = 1 \\
\boldsymbol{\mu}^{\mathrm{T}} \cdot \mathbf{Y} + \mathbf{v}^T \cdot \mathbf{X} + u_k \cdot \mathbf{J} \geq \mathbf{0} \\
\boldsymbol{\mu}^{\mathrm{T}} \geq \varepsilon \mathbf{J} \\
\mathbf{v}^{\mathrm{T}} \geq \varepsilon \mathbf{J}
\end{gathered} \tag{4}$$

where $\mathbf{X}$ – is an input matrix (NxM), $\mathbf{Y}$ – output matrix (NxS), $\mathbf{x}_k$ – vector of inputs for *k-th* DMU (1 x M), $\mathbf{y}_k$ – vector of outputs for *k-th* DMU (1 x S), $\boldsymbol{\lambda}$ – vector of liner combination coefficients, $\mathbf{s}^+$, $\mathbf{s}^-$ - vectors of slacks and surpluses, $\boldsymbol{\mu}$ – vector of outputs weights (1 x S), $\mathbf{v}$ – vector of inputs weights (1 x M), θ – efficiency coefficient of *k-th* DMU, $\mathbf{J}$ – vector of ones, ε - infinitesimal value for forestalling weights to be equal to zero.

For each DMU the model generates an efficiency coefficient θ, vector of slacks $\mathbf{s}^-$ and surpluses $\mathbf{s}^+$ as well as information on returns to scales (constant, increasing or decreasing). For inefficient units the formula for achieving effectiveness (ceteris paribus) is as follows:

$$(\mathbf{x}_k - \mathbf{s}^-; \theta \cdot \mathbf{y}_k + \mathbf{s}^+) \tag{5}$$

While DEA was created for the problem of classical production, this concept has been extended over the years. Firstly, regions are not “factories”, and yet they use resources as effectively and efficiently as possible in order to obtain goals defined by law, social policy, and public expectations. They are governed by elected representatives, who are chosen by the people and for the people. As such they can be treated as a homogenous object and compared by DEA methods and used to establish a spatial efficiency frontier. (Galinienė, Dzemydaitė

2012, pp. 390-399) Secondly, the DEA approach has been used with much success for many topics which are not strictly productive, like health care, public safety, and logistics. (See Suzuki, Nijkamp 2011; Żółtaszek 2014a; Żółtaszek 2014b; Galinienė, Dzemydaitė 2012) It should be mentioned that the DEA model makes it possible to measure relative effectiveness, so values of the efficiency coefficient cannot be compared over time and each year's results should be treated as static.

Since innovation is not an actual production, but a creative process, it should not be treated as fixed and repetitive over time and space. Therefore, out of the available DEA models, a BCC (output oriented) approach with variable returns to scale is introduced. It is assumed that inputs are not utilized in the same way, so in some cases an increase in resources may cause a smaller and in others a larger change of effects in a DMU.

While the DEA methodology was primarily introduced to examine the efficiency, effectiveness, or productivity of companies, it has been gaining popularity among regionalists as well. In general, regions are treated as factories, which operate with limited resources and aim to maximize some tangible effects. Nowadays this approach is used for analysis and comparison of efficiency as well as to detect spatial patterns. Wang and Feng (2015) used DEA methods to research the productivity and economic growth in Chinese regions by analysing three components: input inefficiency, economic output inefficiency, and environmental inefficiency. Dzemydaitė and Galinienė used the DEA approach to analyse regional inequalities in planning infrastructure and human capital development (Galinienė, Dzemydaitė 2012, Dzemydaitė, Galinienė, 2013). Athanassopoulos (1996) analysed the social and economic disadvantages of European regions, where "(…) a region will be comparatively disadvantaged if there is another region or combination of regions with a similar or worse socio-demographic profile that deliver(s) higher levels of social and economic value." (Athanassopoulos, 1996, p.442) In most of the available papers, DEA is used on regional data to establish spatial patterns. However, lately DEA analyses are being paired with other methods in order to better pinpoint the spatial regularities. Lao and Liu (2009) combined GIS (Geographic Information Systems) and the DEA method to assess: firstly, the demographic profiles (using GIS), and then the efficiency (DEA) of each bus line in California (Monterey-Salinas Transit). Kapfer, Kantelhardt, Eckstein, and Hübner (2013) also used both GIS and DEA to measure the performance of agricultural land plots in terms of economy and production. Moreover, the authors assumed that DEA results do not take into account environmental and spatial aspects. Therefore, in the second stage of research the efficiency coefficient was modelled using a Tobit model to explain the differences in the productivity in land plots in the region Rhön in northern Bavaria, Germany. Schaffer, Simar, and Rauland similarly started with a DEA approach and then modelled the calculated efficiency with geo-additive regression incorporating the spatial weight matrix **W**. On the other hand, Maté-Sánchez-Val and Madrid-Guijarro (2011) modified the original data by incorporating the spatial effect by weighting inputs and outputs with the **W** matrix. Afterward they used a fitted DEA model to solve the optimization problem with spatial interactions.

Combining DEA with ESDA techniques is a relatively new approach to the efficiency analysis of regions. Results of DEA models (efficiency coefficients) are tested for spatial autocorrelation (local and global) in order to verify spatial patterns and clusters of efficiency/productivity. Angeriz, Mccombie, and Roberts, (2006) used this combined methodology to assess manufacturing productivity in 68 European NUTS 1 regions. Similarly, Mokaddem (2015) used DEA analysis and spatial autocorrelation, as well as the spatial econometric model, for pinpointing spatial patterns and dependencies of economic development across 252 Tunisian delegations. This novel approach is also utilized in our paper. While DEA analysis is the focal point of regional innovation assessment, the results for NUTS 2 are afterwards tested for global and local autocorrelation of their efficiency.

In order to verify if there is any spatial autocorrelation of innovation efficiency, local and global Moran's I statistics are used. The local Moran's I_i statistic shows whether the i-th location is surrounded by locations with similar (positive spatial autocorrelation) or significantly different values (negative spatial autocorrelation). (Moran, 1947; Cliff and Ord, 1981) The local Moran's I_i statistic is the base for Local Indicators of Spatial Association – LISA. The local Moran's I statistic takes the following form:

$$I_i = \frac{(x_i - \bar{\boldsymbol{x}})}{\frac{1}{N}\sum_{j=1}^{N}(x_j - \bar{\boldsymbol{x}})^2} \sum_{j=1}^{N} w_{ij}(x_j - \bar{\boldsymbol{x}}). \tag{6}$$

with x_i representing the variable in question, $\bar{\boldsymbol{x}}$ its mean. Symbol w_{ij} represents an element of the **W** – spatial weight matrix. The global Moran's I measures general regional similarity for all regions as a mean of local Moran's I_i statistics. The global Moran's I statistic can be presented as follows:

$$I = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}(x_i - \bar{\boldsymbol{x}})(x_j - \bar{\boldsymbol{x}})}{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{\boldsymbol{x}})^2}, \tag{7}$$

We assume a positive spatial autocorrelation if: $I > -\frac{1}{N-1}$ and negative spatial autocorrelation otherwise.The spatial analysis is based on the contiguity spatial weight matrix (Anselin, 1988).

3. Data

In order to measure the efficiency of innovations of European regions using the DEA approach, two inputs and two outputs have been introduced. It is assumed that the "innovation factories", defined as European countries or EU provinces (defined as NUTS 2 regions) use:

- highly qualified human capital, measured by employment in technology and knowledge-intensive sectors per million of the economically active persons (population);
- financial resources defined by total intramural research and development (R&D) expenditure in Purchasing Power Standard (PPS) per economically active person (population) at constant 2010 prices (Euro PPS).

The "products" of innovations are defined as:

- patents, measured as the number of patent applications to the European Patent Office (EPO) by priority year per million economically active persons (population);
- Gross domestic product (GDP) in Purchasing Power Standard (PPS) per economically active persons (population) at constant 2010 prices (Euro PPS) - henceforth denoted as GDP per capita.

Original Eurostat variables were transformed to allow for regional comparisons, using information on the total population, fraction of economically active population, expenditure price index 2005 – 2010, and a GDP fixed base price index. The Eurostat database made it possible to include all 28 member states (Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Rep., Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxemburg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, and the UK) for the years 2000 to 2014. Some missing data had to be extrapolated using the assumption of constant average change rate. The basic statistics on inputs and outputs for the 28 European states and NUTS 2 regions are presented in Table 1 and Table 2.

Table. 1 Basic statistics on inputs and outputs for the 28 European states in years 2000 and 2014

Year	Variable \ Statistic	R&D expenditure in PPS per economically active person at constant 2010 prices (€ PPS)	Employment in technology and knowledge-intensive sectors per million economically active persons	Number of patent applications to the EPO per million economically active persons	GDP PPS per economically active person at constant 2010 prices (€ PPS)
2000	average	671.50	904.69	160.03	50.60
	median	402.80	915.47	37.69	51.86
	Vs	94.05%	5.32%	121.18%	48.75%
	min	54.40	809.21	0.52	19.39
	max	2130.99	977.32	558.74	148.94
2014	average	904.02	893.16	180.96	52.51
	median	675.10	910.55	69.99	48.19
	Vs	70.31%	5.96%	114.72%	40.77%
	min	116.25	733.38	7.69	25.40
	max	1929.74	946.95	691.52	139.46

Source: own computations, based on Eurostat Database. (Vs - variation coefficient based on standard deviation)

In the year 2000, on average each EU 28 state spent € 671.50 (per economically active person) on R&D, however the median indicates that half of the countries allocated no more than € 402.80. This suggests that the distribution of R&D expenses are skewed. The high relative standard deviation (94%) and minimal value (€ 54 in Romania) being over 40 times smaller than the maximum value (€ 2130 in Sweden) confirm a large dispersion. Over time the dispersion in R&D expenses declined (in 2014 the variation coefficient was 70%, and the relation of maximal to minimal value, for Sweden and Romania respectfully, was smaller than 20).

Employment in technology and knowledge-intensive sectors was very evenly distributed over the 28 member states and stable over time (2000-2014). On average, there are around 900 employees (per million) in this sector, measured by the mean and median, with very little dispersion (variation coefficient of 5-6%).

The number of patent applications to the EPO increased over time and is strongly diverse across countries. While the average number of patents increased from 160 in 2000 to 180 in 2014, the median of 38 in 2000 and 70 in 2014 shows a large asymmetry of the distribution. Additionally, the relative standard deviation confirms considerable dispersion (121% in 2000, 115% in 2015). In the year 2000 the minimal number for patents (0.52 (per million persons) in Romania) is over 1100 times smaller than the maximum number for

Germany. In 2014 this ratio was much smaller, around 90, with Croatia (7.7) at the bottom and Finland (692) at the top of the list.

GDP per capita in general has been stable over time and characterised by a symmetric distribution with moderate dispersion. On average (by mean and median) each country generates around €50 per capita, with dispersion less than 50%. The highest value can be observed for Luxemburg, while the lowest was for Romania (2000) and Bulgaria (2014).

The regional analysis was performed for 261 NUTS 2 regions, and for the EU 28 (with the exception of Croatia, due to the unavailability of data). The problem of missing data narrowed the research period to the year 2012, for which the most recent data are available.

Tab. 2 Basic statistics of inputs and outputs for NUTS 2 regions, 2012

Year	Variable \ Statistic	R&D expenditure in PPS per economically active person at constant 2010 prices (€ PPS)	Employment in technology and knowledge-intensive sectors per million economically active persons	Number of patent applications to the EPO per million economically active persons	GDP PPS per economically active person at constant 2010 prices (€ PPS)
2012	average	788.11	904.94	171.02	44.01
	median	547.61	920.02	108.82	47.70
	Vs	104.92%	7.51%	115.94%	51.13%
	min	11.27	649.18	$7 \cdot 10^{-6}$	4.10
	max	6697.77	1106.72	1124.14	177.37

Source: own computations, based on Eurostat Database. (Vs - variation coefficient based on standard deviation)

In analysing the distribution of four input and output variables for NUTS 2 regions, it can be observed that average values (means and medians) are similar to the country-level distribution. The skewness of R&D expenditures is stronger for countries, but weaker for the number of patents. Also, for NUTS 2 regions all variables show more dispersion at the higher level of aggregation, which is no surprise as micro-data are typically less homogenous.

4. Results

In order to analyse the regional effectiveness of innovations, a DEA analysis was performed. The BCC output-oriented model, with 2 inputs and 2 outputs, has been used for the EU28 during the years 2000-2014 (outcomes for exterior years are presented below). The analogical approach has been incorporated for NUTS 2 regions for year 2012. Complete results for the EU28 for the years 2000, 2007, 2012, and 2014, as well as the EU NUTS 2 regions for 2012 are available in the Appendix. All calculations were carried out in STATA MP and visualisations were created in QGIS.

4.1 Results for the 28 EU countries in 2000-2014

Research into the regional effectiveness of innovations of EU member states divides the countries into two categories: efficient (with efficiency coefficient θ equal 100%), and inefficient (with θ>100%). (see Fig.1 and Appendixes 1-4). The analysis shows that for most of the researched period, out of the 28 states around 10 were fully efficient, i.e. they fully utilized their inputs to "produce" outputs of innovations. The rest of the countries could have performed better by increasing their outputs and decreasing some inputs, according to formula 8 (a projection to efficiency frontier or "recipe for efficiency"). For instance, the Czech Republic in the year 2014 has an efficiency coefficient θ equal 171.7%. Therefore, with its level of inputs the state could have produced 171.7% of the actual outputs (i.e. increased both outputs by 71.7%). Moreover, one of the outputs (number of patents) could have been additionally increased by 16.79 units (as the vector of surpluses $\mathbf{s}^+$ indicates) and one of the inputs (employment in technology and knowledge-intensive sectors) should have been lower by 58.11 units (as the vector of slacks $\mathbf{s}^-$ indicates). Altogether the optimal values of Czech's variables should be as follows (see Appendix 4 and formula 8):

$$(\mathbf{x}_{Czech} - \mathbf{s}^-; \theta \cdot \mathbf{y}_{Czech} + \mathbf{s}^+) =$$

$$= ([835.57 \quad 936.98] - [0 \quad 58.11]\,;\, 171.7\% \cdot [50.21 \quad 48.19] + [16.77 \quad 0]) =$$

$$= ([835.57 \quad 878.87];\, [102.98 \quad 48.19]) \tag{8}$$

where $\mathbf{x}_{Czech} = [835.57 \quad 936.98]$ is the vector of the actual (historic) inputs with R&D expenditure as $x_1$and Employment in technology and knowledge-intensive sectors as x_2; and $\mathbf{y}_{Czech} = [50.21 \quad 48.19]$ is the vector of actual (historic) outputs with number of patent applications as y_1 and GDP per capita as y_2.

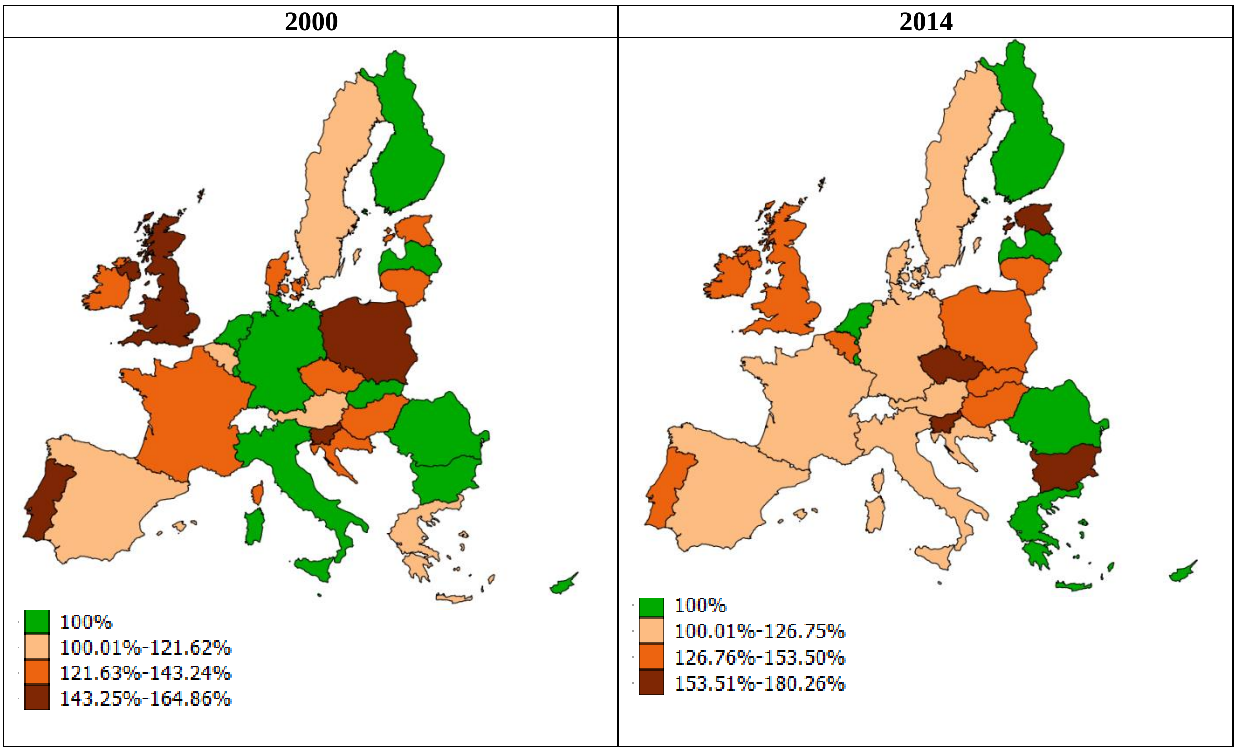


Figure 1. Efficiency coefficient [%] by country in the years 2000 and 2014

Source: own work in QGIS, STATA MP DEA BCC output-oriented model results.

Figure 1 illustrates the efficiency coefficients of the EU28 countries in years 2000 and 2014. Over this period the number of fully efficient countries, i.e. that achieved their innovation potential, decreased from 10-11 (up to 2012) to 7 (in 2014). In 2000 the leaders of innovation were: Bulgaria, Cyprus, Finland, Italy, Latvia, Luxemburg, Malta, the Netherlands, Romania, and Slovakia. In 2014 the most efficient states were: Cyprus, Finland, Greece, Latvia, Luxemburg, the Netherlands, and Romania. Overall, only Cyprus, Luxemburg, and the Netherlands continued to be efficiency leaders of EU throughout the entire period (see Figure 1 and Appendixes 1-4). In the meantime, the level of inefficiency, as measured by the efficiency coefficient, kept growing. The worst performing countries underachieved their goals (patents and GDP per capita) by 60-122%. The lowest performance (by top three values of the efficiency coefficient) can be observed for Estonia since 2007, the Czech Republic since 2012, and, on and off Slovenia, Poland, and Portugal. It is also interesting that the number of countries with extreme values (i.e. both fully efficient and very inefficient) declined over time. This suggests either that the efficiency of innovations regress to the centre values, or alternatively a convergence thereof across EU states.

Taking into consideration the variable returns to scale of innovation efficiency, it is clear that the pace of intellectual progress is decreasing (see Figure 2 and Appendixes 1-4). In year 2000, 18 out of 28 countries had increasing returns to scale, which enabled a more than proportional growth of outputs for each 1% increase of inputs. Over time, the number of increasing returns to scale has outpaced by decreasing returns (13 states in 2014). Moreover, a pattern has emerged where the countries of Western Europe still maintain increasing returns, while the Central-Eastern countries have decreasing or constant effects. For states with decreasing returns to scale, the outcomes of innovations are more slow (or less than proportional) than the inputs. Thus growing expenses and employment in the R&D sector do not translate into a higher efficiency of innovations.

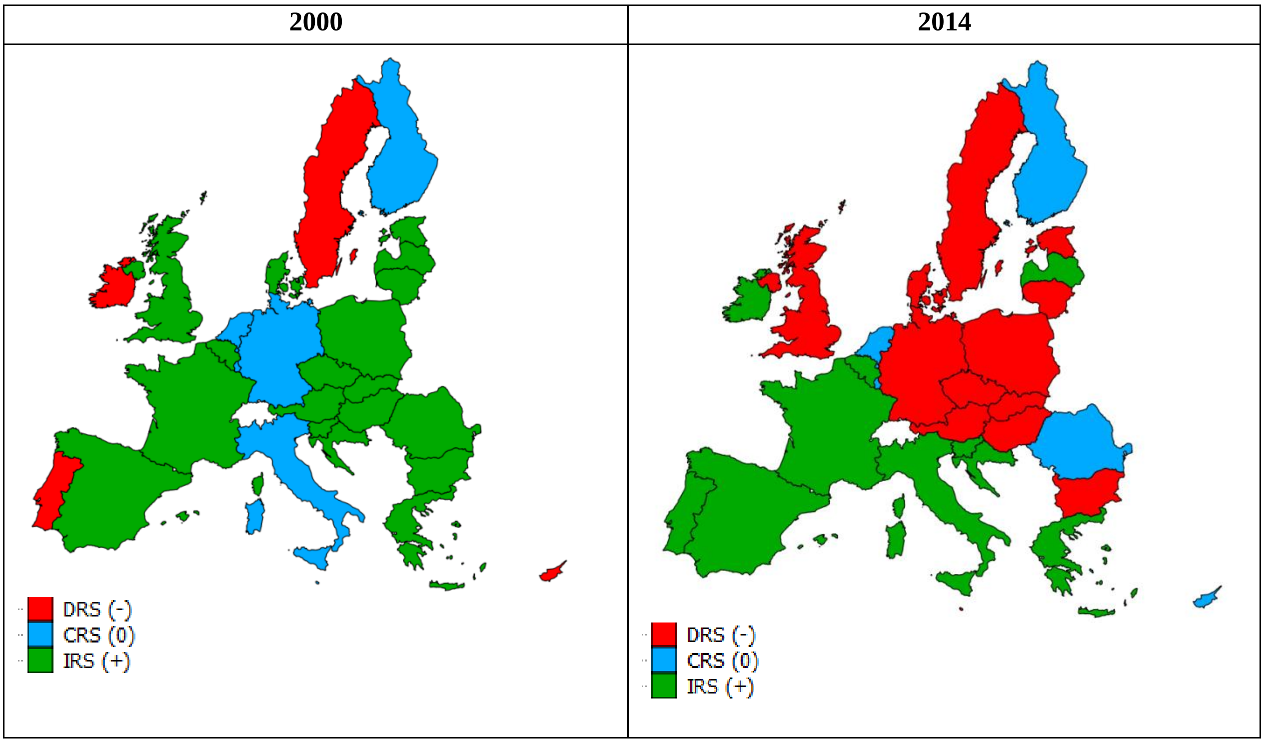


Figure 2. returns to scale (DRS- decreasing, CRS-constant, INS-increasing) by country in years 2000 and 2014

Source: own work in QGIS, STATA MP DEA BCC output-oriented model results.

4.2. Results for EU NUTS 2 regions in 2012

The next step of the analysis is the application of an analogical approach for EU NUTS 2 regions for 2012 with NUTS 0 as benchmarks. It can be observed that the regional distribution of innovation efficiency is much different. (see Figure 3 and Appendixes 3 & 5)

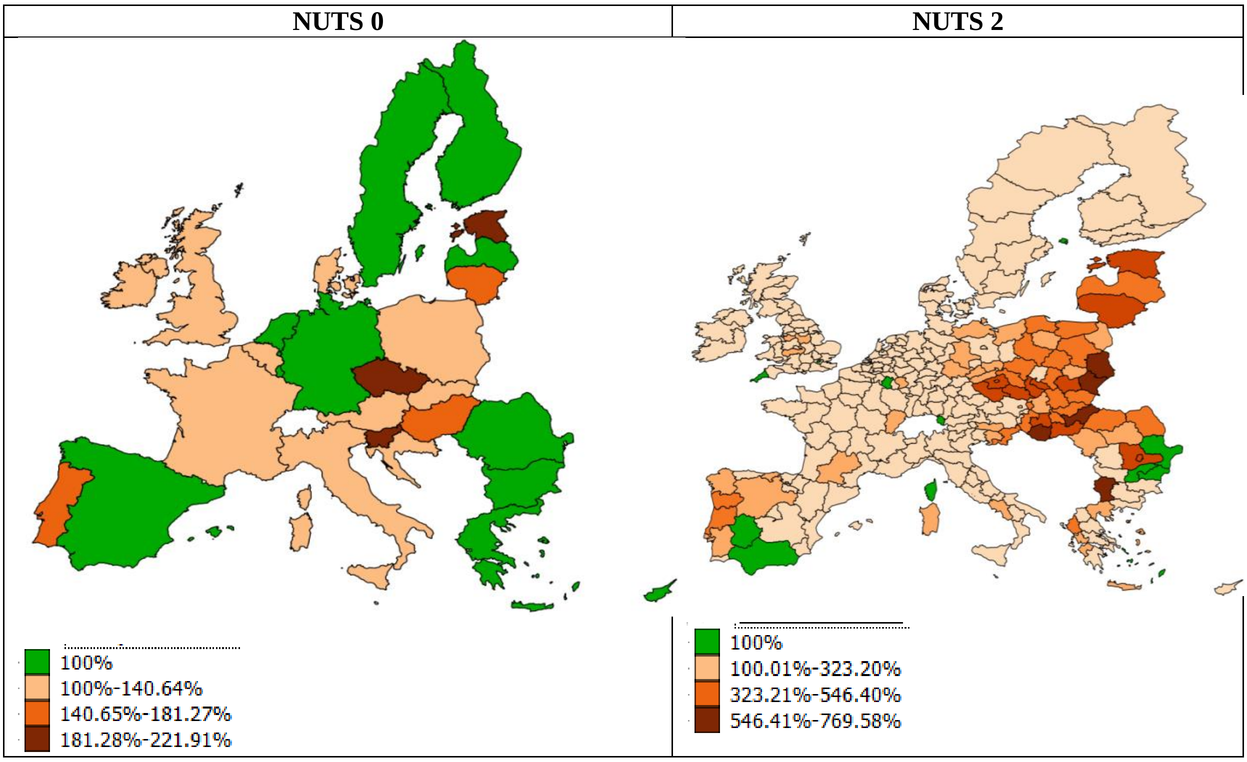


Figure 3. Efficiency coefficient [%] by EU NUTS 0 and NUTS 2 regions in year 2012

Source: own work in QGIS, STATA MP DEA BCC output-oriented model results.

In 2012, 11 of 28 countries were efficient, while the worst performing region had an efficiency coefficient of 222% (Estonia). Out of 261 provinces only 12 were fully efficient in their innovations: Vorarlberg (Austria), Luxembourg (Belgium), Severen tsentralen (Bulgaria), Severoiztochen (Bulgaria), South Aegean (Greece), Extremadura (Spain), Andalusia (Spain), Åland (Finland), Corsica (France), Sud-Est (Romenia), Inner London (UK), and Cornwall and the Isles of Scilly (UK). The maximum inefficiency can be observed at 769.6%, which means that the number of patents and GDP per active person could have been 7.5 times higher with given inputs, with the worst performing regions being: Yugozapaden with Sofia (Bulgaria), Southern Transdanubia (Hungary), Northern Great Plain (Hungary), Lubelskie and Podkarpackie (Poland). The diversity of innovations (measured by efficiency) is much higher for NUTS 2 regions than for countries. Only 4.5% of provinces are fully realizing their innovation potential. (see Figure 3 and Appendixes 3 & 5)

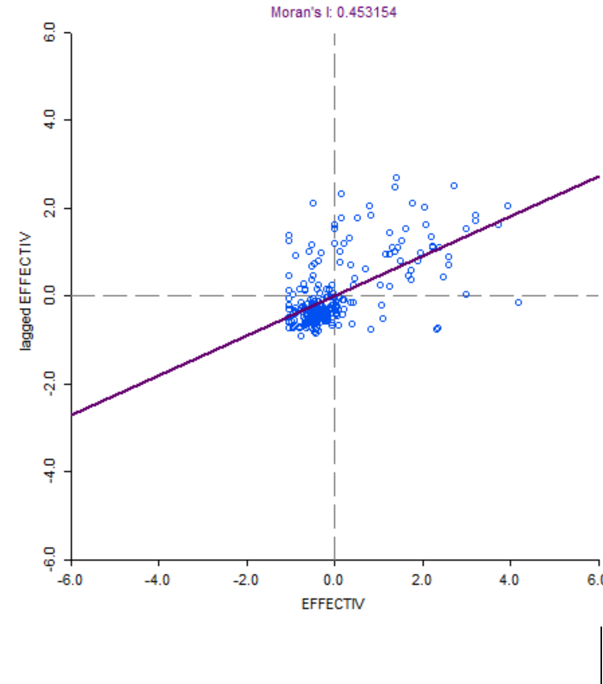
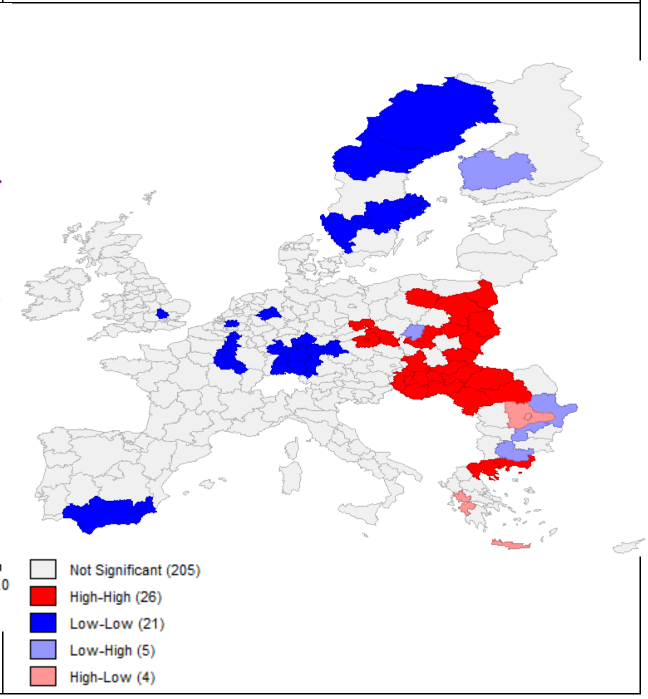
Global Moran's *I* and scatter plot	**LISA**
	

Figure 4. Spatial autocorrelation analysis of efficiency coefficient for innovations by NUTS 2 regions for the year 2012

Source: own work in GeoDa, based on STATA MP results for DEA BCC output-oriented model.

Figure 4 presents the results of the autocorrelation analysis. The spatial autocorrelation of innovation effectiveness for NUTS2 regions in year 2012 is high, with Moran's I=0.45. This means that on average, innovation effectiveness in one region is similar to the effectiveness in the bordering regions. This is also reflected by the local indicator of spatial autocorrelation. Figure 4 (on the right) presents the LISA cluster map of effectiveness. We can observe here 26 hot-spots and 21 cold-spots. The former are regions with a high efficiency coefficient, which indicates a poor performance in innovations, which coincides with similar high levels of coefficient θ for their neighbours. These high-high clusters are located mainly in Central and Eastern Europe, namely in: Germany, the Czech Republic, Poland, Slovakia, Hungary, Romania, and Greece. The cold-spots, or low-low clusters, are regions with a low efficiency coefficient, hence fully efficient or close to full efficiency, and also surrounded by similar regions. These low-low clusters are located mainly in Western Europe, including regions in: Sweden, Germany, Netherlands, Belgium, Luxemburg, France, UK (around London), and Spain. Therefore, the efficiency of innovations has a statistically significant spatial pattern. In general, low efficiency (i.e. a high efficiency coefficient) is more typical for Central and Eastern Europe, while high efficiency (represented by a lower efficiency coefficient) is located primarily in Western Europe.

Figure 5 presents the returns to scale of efficiency of innovations by province. In terms of countries there are 16 out of 28 (almost 60%) with increasing returns to scale, mainly in Western Europe, the Balkans, and the Baltic States (decreasing and content effects in six countries). Among the 11 efficient states, six have constant returns to scale, four increasing, and one decreasing. In the analysis for NUTS 2 regions almost 70% of regions (180 of 261) have decreasing returns to scale, 28% have increasing returns, and only 3% constant. However, this 3% (seven regions) have efficiency of 100%, while the remaining five efficient regions have increasing returns to scale. Overall constant returns to scale are typical only for efficient regions (both for NUTS 0 and NUTS 2). Also, some leaders of innovations have increasing economies of scale. In the NUTS 2 analysis almost 70% of provinces have decreasing returns to scale, which indicates a slower than proportional increase in innovations compared to the increase of inputs. In Spain, Finland, Latvia, Slovakia, Hungary, and Greece increasing returns to scale characterise all or most of the countries' provinces, which result in similar returns as the NUTS 0 level. In Germany, the UK, the Czech Republic, Austria, Netherlands, Belgium, and Luxemburg, almost all provinces have decreasing returns to scale, therefore their total result for NUTS 0 is the same. However, France, Belgium, Slovenia and Italy, despite having decreasing returns at the NUTS 2 level, altogether have increasing returns to scale at the NUTS 0 level.

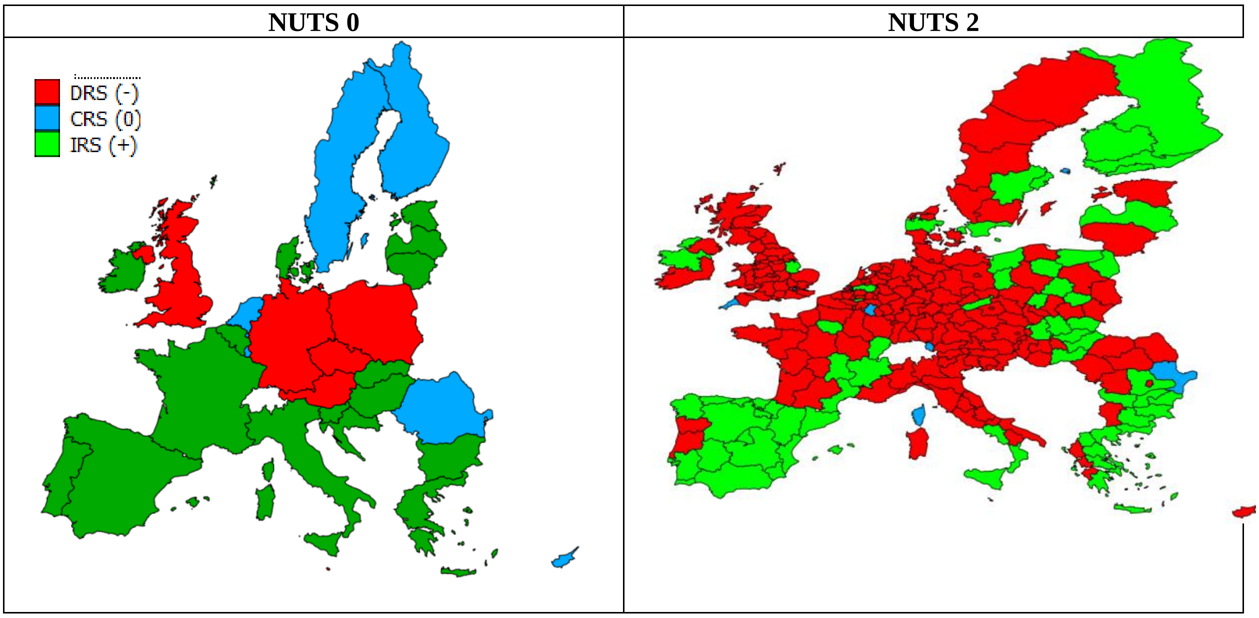


Figure 5. Returns to scale (DRS- decreasing, CRS-constant, INS-increasing) by NUTS 0 and NUTS 2 regions in year 2012

Source: own work in QGIS, STATA MP DEA BCC output-oriented model results,.

5. Conclusions

In this paper we employed a strictly quantitative analysis to the problem of regional innovation potential. The DEA model made it possible to measure the effectiveness of innovations in the EU28 countries and in 261 regions over the long run. Unlike the more typical approaches, the DEA model does not assess the level of innovations, but the percentage of realized potential of innovations. Therefore it is possible that both high innovative regions (connecting high inputs with high outputs, e.g. Germany, Scandinavia) and low innovative ones (with low inputs and low outputs, e.g. the Balkans) fully utilize their potential and perform effectively. On the other hand, if high/low inputs do not correspond with a proportional level of outputs, a region is underperforming and wasting its innovative potential. The DEA results are relative (always referring to the set of regions included in the research) and static (which diminishes the possibility of analysing effectiveness over time).

The performed efficiency analysis indicates that the number of regions which fully utilize their innovative potential is decreasing over time. In particular the research for NUTS 2 provinces shows less than 5% of efficient regions, scattered across the EU, while for countries 25%-40% perform exemplary. However, expanding the DEA analysis by spatial statistics resulted in pinpointing the spatial patterns in the distribution of innovation efficiency (for NUTS 2 regions, as the state level has too few objects). Central and Eastern Europe (including parts of Germany, the Czech Republic, Poland, Slovakia, Hungary, Romania, and Greece) contain a considerable cluster of high efficiency. These regions realize their innovative potential to a very high degree (but not fully). Conversely, low innovative clusters are typical for Western Europe (notably parts of: Sweden, Germany, the Netherlands, Belgium, Luxemburg, France, the UK, and Spain), where regions underachieve their innovative potential. These results are largely contradictory with the European Commission’s Regional Innovation Scoreboard, which pinpoints NUTS 2 regions in Scandinavia, Germany, France and UK as innovation leaders or strong innovators, while Central and Eastern Europe is characterised as having moderate and modest innovators. (European Innovation Scoreboard, 2016) These dissimilarities may suggest that it is easier to highly utilize the innovative potential for regions if there is a lower level of innovations.

Comparison of the regional and country efficiency indicates a vast effectiveness gap for NUTS 2 regions, compared to a much smaller diversity for countries. The dispersion of ineffectiveness is increasing over time. Moreover, the main source of inefficiency for states are too few patents to EPO (output), but for NUTS 2 the sources of inefficiency are too high employment in technology and knowledge-intensive sectors as well as R&D expenses (inputs).

The DEA analysis also included returns to scale, which indirectly incorporates the qualitative aspect of innovations. This aspect shows the expected effect of increasing inputs on innovations (R&D expenses and human capital). Over the time (i.e. from 2000 to 2014) the dynamics of returns to scale slowly switched from increasing to decreasing. Most countries and regions achieve, by increasing their inputs, less than proportional increases of outputs. Moreover, regional and state returns to scale overlap for the majority of countries. These results suggest that returns to scale have a country-specific element. The distribution of returns to scale corresponds neither with the level of innovations (European Innovation Scoreboard, 2016) nor the efficiency of innovations (DEA results). This strengthens the possibility that specific factors are involved.

In conclusion, the DEA analysis made it possible to indicate leaders and followers (at the NUTS 0 and NUTS 2 level) in innovations, as well as the main sources of lost efficiency. However it does not take into account any quality-based aspects, like creativity of the innovation process, the structure of R&D organizations (companies, research facilities, universities), and the types of innovations. Therefore, it would be beneficial to conduct complementary research, including social, educational, and legal factors, to cross-reference the results and conclusions.

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Appendix 1. Results of DEA BCC output-oriented model for the EU28 in year 2000

DMU: NUTS 0	Efficiency coefficient Θ [%]	Additional inputs reduction (slacks s^-)		Additional outputs increase (surpluses s^+)		returns to scale: DRS(-)-decreasing, CRS(0) – constant, IRS(+) increasing
		R&D expenditure in PPS per economically active person at constant 2010 prices (€ PPS)	Employment in technology and knowledge-intensive sectors per million economically active persons	Number of patent applications to the EPO per million economically active persons	GDP PPS per economically active person at constant 2010 prices (€ PPS)	
Austria	120.7%	0	0	0	0	IRS(+)
Belgium	120.9%	0	0	0	0	IRS(+)
Bulgaria	100.0%	0	0	0	0	IRS(+)
Croatia	136.3%	0	0	9.40691	0	IRS(+)
Cyprus	100.0%	N/A	N/A	N/A	N/A	DRS(-)
Czech	123.4%	0	0	54.3346	0	IRS(+)
Denmark	124.6%	0	0	0	0	IRS(+)
Estonia	134.1%	0	0	.947254	0	IRS(+)
Finland	100.0%	N/A	N/A	N/A	N/A	CRS(0)
France	122.3%	0	0	0	0	IRS(+)
Germany	100.0%	N/A	N/A	N/A	N/A	CRS(0)
Greece	100.2%	0	0	31.7506	0	IRS(+)
Hungary	143.2%	0	0	18.372	0	IRS(+)
Ireland	125.2%	0	3.31483	0	0	DRS(-)
Italy	100.0%	0	0	0	0	CRS(0)
Latvia	100.0%	N/A	N/A	N/A	N/A	IRS(+)
Lithuania	132.9%	0	0	1.75971	0	IRS(+)
Lux	100.0%	N/A	N/A	N/A	N/A	CRS(0)
Malta	100.0%	N/A	N/A	N/A	N/A	CRS(0)
Netherl	100.0%	N/A	N/A	N/A	N/A	CRS(0)
Poland	153.3%	0	0	7.11879	0	IRS(+)
Portugal	153.1%	0	0.517571	41.2599	0	DRS(-)
Romania	100.0%	N/A	N/A	N/A	N/A	IRS(+)
Slovakia	100.0%	N/A	N/A	N/A	N/A	IRS(+)
Slovenia	164.9%	0	0	14.7342	0	IRS(+)
Spain	102.4%	0	0	31.901	0	IRS(+)
Sweden	107.1%	718.723	22.4561	0	0	DRS(-)
UK	147.1%	0	0	0	0	IRS(+)

Source: own work. (N/A – for DMUs with 100% efficiency coefficient no additional changes of inputs and/or outputs are offered)

Appendix 2. Results of DEA BCC output-oriented model for the EU28 in year 2007

DMU: NUTS 0	Efficiency coefficient Θ [%]	Additional inputs reduction (slacks s^-)		Additional output increase (surpluses s^+)		returns to scale: DRS(-)-decreasing, CRS(0) – constant, IRS(+) increasing
		R&D expenditure in PPS per economically active person at constant 2010 prices	Employment in technology and knowledge-intensive sectors per million	Number of patent applications to the EPO per million economically active persons	GDP PPS per economically active person at constant 2010 prices (€ PPS)	

		(€ PPS)	economically active persons			
Austria	121.2%	0	41.3228	0	0	DRS(-)
Belgium	110.9%	0	0	0	0	IRS(+)
Bulgaria	100.0%	N/A	N/A	N/A	N/A	CRS(0)
Croatia	100.0%	N/A	N/A	N/A	N/A	IRS(+)
Cyprus	100.0%	N/A	N/A	N/A	N/A	CRS(0)
Czech	142.6%	0	0	16.7243	0	DRS(-)
Denmark	120.7%	0	36.5305	0	0	DRS(-)
Estonia	161.0%	0	0	0	0	IRS(+)
Finland	117.5%	229.525	0	0	0	DRS(-)
France	114.5%	0	0	0	0	IRS(+)
Germany	100.0%	N/A	N/A	N/A	N/A	CRS(0)
Greece	100.0%	N/A	N/A	N/A	N/A	CRS(0)
Hungary	153.7%	0	0	0	0	IRS(+)
Ireland	116.3%	0	0	0	0	IRS(+)
Italy	100.0%	N/A	N/A	N/A	N/A	CRS(0)
Latvia	140.3%	0	49.0015	0	0	IRS(+)
Lithuania	157.2%	0	54.6649	25.595	0	DRS(-)
Lux	100.0%	N/A	N/A	N/A	N/A	CRS(0)
Malta	101.4%	0	0	0	0	IRS(+)
Netherl	100.0%	N/A	N/A	N/A	N/A	CRS(0)
Poland	136.5%	0	0	.725764	0	IRS(+)
Portugal	157.9%	0	0	9.92103	0	DRS(-)
Romania	150.0%	0	0	4.86058	0	IRS(+)
Slovakia	100.0%	N/A	N/A	N/A	N/A	IRS(+)
Slovenia	135.5%	0	0	0	0	IRS(+)
Spain	129.3%	0	0	0	0	IRS(+)
Sweden	100.0%	N/A	N/A	N/A	N/A	DRS(-)
UK	139.8%	0	0	0	0	IRS(+)

Source: own work. (N/A – for DMUs with 100% efficiency coefficient no additional changes of inputs and/or outputs are offered)

Appendix 3. Results of DEA BCC output-oriented model for the EU28 in year 2012

DMU: NUTS 0	Efficiency coefficient *Θ* [%]	Additional inputs reduction (slacks s^-)		Additional output increase (surpluses s^+)		returns to scale: DRS(-)-decreasing, CRS(0) – constant, IRS(+) increasing
		R&D expenditure in PPS per economically active person at constant 2010 prices (€ PPS)	Employment in technology and knowledge-intensive sectors per million economically active persons	Number of patent applications to the EPO per million economically active persons	GDP PPS per economically active person at constant 2010 prices (€ PPS)	
Austria	117.0%	0	15.1926	0	0	DRS(-)
Belgium	127.0%	0	0	0	0	IRS(+)
Bulgaria	100.0%	N/A	N/A	N/A	N/A	IRS(+)
Croatia	127.3%	0	0	.0204397	0	IRS(+)
Cyprus	100.0%	N/A	N/A	N/A	N/A	CRS(0)
Czech	181.6%	0	26.8135	19.8014	0	DRS(-)
Denmark	114.8%	0	0	0	0	IRS(+)
Estonia	221.9%	0	0	23.358	0	IRS(+)
Finland	100.0%	N/A	N/A	N/A	N/A	CRS(0)

France	113.3%	0	0	0	0	IRS(+)
Germany	100.0%	N/A	N/A	N/A	N/A	DRS(-)
Greece	100.0%	N/A	N/A	N/A	N/A	IRS(+)
Hungary	149.1%	0	0	0	0	IRS(+)
Ireland	123.7%	0	0	0	0	IRS(+)
Italy	101.5%	0	0	0	0	IRS(+)
Latvia	100.0%	N/A	N/A	N/A	N/A	IRS(+)
Lithuania	143.9%	0	0	0	0	IRS(+)
Lux	100.0%	N/A	N/A	N/A	N/A	CRS(0)
Malta	121.5%	0	46.8385	13.8669	0	DRS(-)
Netherl	100.0%	N/A	N/A	N/A	N/A	CRS(0)
Poland	131.7%	0	13.3248	0	0	DRS(-)
Portugal	151.5%	0	0	28.9367	0	IRS(+)
Romania	100.0%	N/A	N/A	N/A	N/A	CRS(0)
Slovakia	133.5%	0	0	3.27385	0	IRS(+)
Slovenia	185.1%	0	0	0	0	IRS(+)
Spain	100.0%	N/A	N/A	N/A	N/A	IRS(+)
Sweden	100.0%	N/A	N/A	N/A	N/A	CRS(0)
UK	129.4%	0	1.72095	0	0	DRS(-)

Source: own work. (N/A – for DMUs with 100% efficiency coefficient no additional changes of inputs and/or outputs are offered)

Appendix 4. Results of DEA BCC output-oriented model for the EU28 in year 2014

DMU: NUTS 0	Efficiency coefficient Θ [%]	Additional inputs reduction (slacks s^-)		Additional output increase (surpluses s^+)		returns to scale: DRS(-)-decreasing, CRS(0) – constant, IRS(+) increasing
		R&D expenditure in PPS per economically active person at constant 2010 prices (€ PPS)	Employment in technology and knowledge-intensive sectors per million economically active persons	Number of patent applications to the EPO per million economically active persons	GDP PPS per economically active person at constant 2010 prices (€ PPS)	
Austria	123.8%	92.6081	19.3605	0	0	DRS(-)
Belgium	137.5%	0	0	0	0	IRS(+)
Bulgaria	162.9%	0	36.287	0	0	DRS(-)
Croatia	125.9%	0	0	10.5029	0	IRS(+)
Cyprus	100.0%	N/A	N/A	N/A	N/A	CRS(0)
Czech	171.7%	0	58.1055	16.7864	0	DRS(-)
Denmark	121.9%	76.137	14.381	0	0	DRS(-)
Estonia	180.3%	0	67.5724	25.2245	0	DRS(-)
Finland	100.0%	N/A	N/A	N/A	N/A	CRS(0)
France	121.4%	0	0	0	0	IRS(+)
Germany	117.5%	0	27.7829	0	0	DRS(-)
Greece	100.0%	N/A	N/A	N/A	N/A	IRS(+)
Hungary	148.7%	0	62.9173	0	0	DRS(-)
Ireland	128.1%	0	0	0	0	IRS(+)
Italy	103.4%	0	0	0	0	IRS(+)
Latvia	100.0%	N/A	N/A	N/A	N/A	IRS(+)
Lithuania	142.7%	0	41.0644	0	0	DRS(-)
Lux	100.0%	N/A	N/A	N/A	N/A	CRS(0)
Malta	120.3%	0	85.6618	21.0444	0	DRS(-)
Netherl	100.0%	N/A	N/A	N/A	N/A	CRS(0)

Poland	128.2%	0	60.0122	0	0	DRS(-)
Portugal	147.7%	0	0	19.3991	0	IRS(+)
Romania	100.0%	N/A	N/A	N/A	N/A	CRS(0)
Slovakia	129.5%	0	21.2088	13.1487	0	DRS(-)
Slovenia	167.7%	0	0	0	0	IRS(+)
Spain	105.6%	81.1889	0	0	0	IRS(+)
Sweden	103.6%	84.9246	6.12823	0	0	DRS(-)
UK	136.6%	0	39.7647	0	0	DRS(-)

Source: own work. (N/A – for DMUs with 100% efficiency coefficient no additional changes of inputs and/or outputs are offered)

Appendix 5. Results of DEA BCC output-oriented model for EU NUTS 2 in year 2012

DMU: NUTS 2	**Efficiency coefficient Θ [%]**	**Additional inputs reduction (slacks s^-)**		**Additional output increase (surpluses s^+)**		**returns to scale: DRS(-)-decreasing. CRS(0) – constant. IRS(+) increasing**
		R&D expenditure in PPS per economically active person at constant 2010 prices (€ PPS)	**Employment in technology and knowledge-intensive sectors per million economically active persons**	**Number of patent applications to the EPO per million economically active persons**	**GDP PPS per economically active person at constant 2010 prices (€ PPS)**	
AT11	185.2%	0	117.884	0	0	CRS(0)
AT12	173.8%	0	84.0204	0	0	CRS(0)
AT13	181.6%	913.227	49.3794	0	0	CRS(0)
AT21	238.2%	0	117.885	0	0	CRS(0)
AT22	184.5%	0	84.0205	0	0	CRS(0)
AT31	168.6%	913.228	49.3795	0	0	CRS(0)
AT32	151.8%	0	117.886	0	0	CRS(0)
AT33	190.3%	0	84.0206	0	0	CRS(0)
AT34	100.0%	N/A	N/A	N/A	N/A	CRS(0)
BE10	115.9%	0	117.887	0	0	IRS(+)
BE21	174.7%	0	84.0207	0	0	CRS(0)
BE22	176.9%	913.230	49.3797	0	0	CRS(0)
BE23	212.5%	0	117.888	0	0	CRS(0)
BE24	158.4%	0	84.0208	0	0	CRS(0)
BE25	164.3%	913.231	49.3798	0	0	CRS(0)
BE31	148.3%	0	117.889	0	0	IRS(+)
BE32	208.7%	0	84.0209	0	0	CRS(0)
BE33	183.9%	913.232	49.3799	0	0	CRS(0)
BE34	100.0%	N/A	N/A	N/A	N/A	CRS(0)
BE35	176.5%	0	84.0210	0	0	CRS(0)
BG31	157.2%	913.233	49.3800	0	0	IRS(+)
BG32	100.0%	N/A	N/A	N/A	N/A	IRS(+)
BG33	100.0%	N/A	N/A	N/A	N/A	IRS(+)
BG34	157.3%	913.234	49.3801	0	0	IRS(+)
BG41	769.6%	0	117.892	0	0	CRS(0)
BG42	233.1%	0	84.0212	0	0	IRS(+)
CY00	198.6%	913.235	49.3802	0	0	CRS(0)
CZ01	394.3%	0	117.893	0	0	CRS(0)
CZ02	516.8%	0	84.0213	0	0	CRS(0)
CZ03	565.0%	913.236	49.3803	0	0	CRS(0)
CZ04	280.3%	0	117.894	0	0	IRS(+)

CZ05	495.0%	0	84.0214	0	0	CRS(0)
CZ06	550.8%	913.237	49.3804	0	0	CRS(0)
CZ07	566.9%	0	117.895	0	0	CRS(0)
CZ08	520.6%	0	84.0215	0	0	CRS(0)
DE11	112.4%	913.238	49.3805	0	0	CRS(0)
DE12	130.3%	0	117.896	0	0	CRS(0)
DE13	142.4%	0	84.0216	0	0	CRS(0)
DE14	135.8%	913.239	49.3806	0	0	CRS(0)
DE21	108.7%	0	117.897	0	0	CRS(0)
DE22	167.6%	0	84.0217	0	0	CRS(0)
DE23	120.5%	913.240	49.3807	0	0	CRS(0)
DE24	168.4%	0	117.898	0	0	CRS(0)
DE25	116.8%	0	84.0218	0	0	CRS(0)
DE26	149.9%	913.241	49.3808	0	0	CRS(0)
DE27	130.1%	0	117.899	0	0	CRS(0)
DE30	209.0%	0	84.0219	0	0	CRS(0)
DE40	217.9%	913.242	49.3809	0	0	CRS(0)
DE50	198.5%	0	117.900	0	0	CRS(0)
DE60	139.8%	0	84.0220	0	0	CRS(0)
DE71	150.4%	913.243	49.3810	0	0	CRS(0)
DE72	196.7%	0	117.901	0	0	CRS(0)
DE73	184.3%	0	84.0221	0	0	CRS(0)
DE80	259.0%	913.244	49.3811	0	0	CRS(0)
DE91	186.1%	0	117.902	0	0	CRS(0)
DE92	183.5%	0	84.0222	0	0	CRS(0)
DE93	171.1%	913.245	49.3812	0	0	CRS(0)
DE94	144.3%	0	117.903	0	0	CRS(0)
DEA1	146.4%	0	84.0223	0	0	CRS(0)
DEA2	170.9%	913.246	49.3813	0	0	CRS(0)
DEA3	145.6%	0	117.904	0	0	CRS(0)
DEA4	152.3%	0	84.0224	0	0	CRS(0)
DEA5	157.1%	913.247	49.3814	0	0	CRS(0)
DEB1	138.2%	0	117.905	0	0	CRS(0)
DEB2	282.5%	0	84.0225	0	0	CRS(0)
DEB3	157.3%	913.248	49.3815	0	0	CRS(0)
DEC0	162.8%	0	117.906	0	0	CRS(0)
DED2	276.6%	0	84.0226	0	0	CRS(0)
DED4	286.7%	913.249	49.3816	0	0	CRS(0)
DED5	224.6%	0	117.907	0	0	CRS(0)
DEE0	238.2%	0	84.0227	0	0	CRS(0)
DEF0	175.3%	913.250	49.3817	0	0	CRS(0)
DEG0	236.2%	0	117.908	0	0	CRS(0)
DK01	150.4%	0	84.0228	0	0	IRS(+)
DK02	176.2%	913.251	49.3818	0	0	CRS(0)
DK03	155.7%	0	117.909	0	0	CRS(0)
DK04	163.3%	0	84.0229	0	0	IRS(+)
DK05	158.1%	913.252	49.3819	0	0	CRS(0)
EE00	615.9%	0	117.910	0	0	CRS(0)
EL11	233.9%	0	84.0230	0	0	IRS(+)
EL12	234.5%	913.253	49.3820	0	0	IRS(+)
EL13	143.1%	0	117.911	0	0	IRS(+)
EL14	220.4%	0	84.0231	0	0	IRS(+)
EL21	375.0%	913.254	49.3821	0	0	CRS(0)
EL22	129.9%	0	117.912	0	0	IRS(+)
EL23	339.6%	0	84.0232	0	0	CRS(0)
EL24	112.9%	913.255	49.3822	0	0	IRS(+)
EL25	173.7%	0	117.913	0	0	IRS(+)
EL30	170.8%	0	84.0233	0	0	IRS(+)

EL41	278.8%	913.256	49.3823	0	0	IRS(+)
EL42	100.0%	N/A	N/A	N/A	N/A	IRS(+)
EL43	245.5%	0	84.0234	0	0	IRS(+)
ES11	247.9%	913.257	49.3824	0	0	IRS(+)
ES12	216.2%	0	117.915	0	0	IRS(+)
ES13	255.0%	0	84.0235	0	0	IRS(+)
ES21	231.0%	913.258	49.3825	0	0	IRS(+)
ES22	222.2%	0	117.916	0	0	IRS(+)
ES23	191.6%	0	84.0236	0	0	IRS(+)
ES24	183.3%	913.259	49.3826	0	0	IRS(+)
ES30	220.0%	0	117.917	0	0	IRS(+)
ES41	247.5%	0	84.0237	0	0	IRS(+)
ES42	119.2%	913.260	49.3827	0	0	IRS(+)
ES43	100.0%	N/A	N/A	N/A	N/A	IRS(+)
ES51	161.0%	0	84.0238	0	0	IRS(+)
ES52	178.2%	913.261	49.3828	0	0	IRS(+)
ES53	144.3%	0	117.919	0	0	IRS(+)
ES61	100.0%	N/A	N/A	N/A	N/A	IRS(+)
ES62	180.2%	913.262	49.3829	0	0	IRS(+)
FI19	168.1%	0	117.920	0	0	IRS(+)
FI1B	118.5%	0	84.0240	0	0	IRS(+)
FI1C	192.1%	913.263	49.3830	0	0	IRS(+)
FI1D	204.6%	0	117.921	0	0	IRS(+)
FI20	100.0%	N/A	N/A	N/A	N/A	CRS(0)
FR10	142.6%	913.264	49.3831	0	0	IRS(+)
FR21	152.5%	0	117.922	0	0	CRS(0)
FR22	203.9%	0	84.0242	0	0	CRS(0)
FR23	173.2%	913.265	49.3832	0	0	CRS(0)
FR24	191.5%	0	117.923	0	0	CRS(0)
FR25	197.2%	0	84.0243	0	0	CRS(0)
FR26	173.9%	913.266	49.3833	0	0	CRS(0)
FR30	176.4%	0	117.924	0	0	CRS(0)
FR41	198.8%	0	84.0244	0	0	CRS(0)
FR42	178.7%	913.267	49.3834	0	0	CRS(0)
FR43	238.2%	0	117.925	0	0	IRS(+)
FR51	179.5%	0	84.0245	0	0	CRS(0)
FR52	194.5%	913.268	49.3835	0	0	CRS(0)
FR53	179.5%	0	117.926	0	0	CRS(0)
FR61	197.7%	0	84.0246	0	0	CRS(0)
FR62	259.0%	913.269	49.3836	0	0	CRS(0)
FR63	187.6%	0	117.927	0	0	CRS(0)
FR71	166.9%	0	84.0247	0	0	IRS(+)
FR72	216.1%	913.270	49.3837	0	0	IRS(+)
FR81	227.1%	0	117.928	0	0	IRS(+)
FR82	205.8%	0	84.0248	0	0	CRS(0)
FR83	100.0%	N/A	N/A	N/A	N/A	CRS(0)
HU10	408.0%	0	117.929	0	0	CRS(0)
HU21	615.9%	0	84.0249	0	0	CRS(0)
HU22	442.8%	913.272	49.3839	0	0	CRS(0)
HU23	645.0%	0	117.930	0	0	CRS(0)
HU31	461.6%	0	84.0250	0	0	IRS(+)
HU32	740.7%	913.273	49.3840	0	0	IRS(+)
HU33	584.0%	0	117.931	0	0	IRS(+)
IE01	199.7%	0	84.0251	0	0	IRS(+)
IE02	171.8%	913.274	49.3841	0	0	CRS(0)
ITC1	213.1%	0	117.932	0	0	CRS(0)
ITC2	135.1%	0	84.0252	0	0	CRS(0)
ITC3	186.3%	913.275	49.3842	0	0	CRS(0)

ITC4	165.3%	0	117.933	0	0	CRS(0)
ITF1	201.7%	0	84.0253	0	0	CRS(0)
ITF2	184.6%	913.276	49.3843	0	0	CRS(0)
ITF3	240.3%	0	117.934	0	0	IRS(+)
ITF4	233.5%	0	84.0254	0	0	CRS(0)
ITF5	207.9%	913.277	49.3844	0	0	CRS(0)
ITF6	215.1%	0	117.935	0	0	IRS(+)
ITG1	230.1%	0	84.0255	0	0	IRS(+)
ITG2	239.7%	913.278	49.3845	0	0	CRS(0)
ITH1	119.9%	0	117.936	0	0	CRS(0)
ITH2	214.2%	0	84.0256	0	0	CRS(0)
ITH3	163.0%	913.279	49.3846	0	0	CRS(0)
ITH4	145.5%	0	117.937	0	0	CRS(0)
ITH5	178.0%	0	84.0257	0	0	CRS(0)
ITI1	189.4%	913.280	49.3847	0	0	CRS(0)
ITI2	199.1%	0	117.938	0	0	CRS(0)
ITI3	180.6%	0	84.0258	0	0	CRS(0)
ITI4	211.6%	913.281	49.3848	0	0	CRS(0)
LT00	540.6%	0	117.939	0	0	CRS(0)
LU00	114.7%	0	84.0259	0	0	CRS(0)
LV00	407.8%	913.282	49.3849	0	0	IRS(+)
MT00	288.3%	0	117.940	0	0	CRS(0)
NL11	172.1%	0	84.0260	0	0	CRS(0)
NL12	195.4%	913.283	49.3850	0	0	CRS(0)
NL13	189.8%	0	117.941	0	0	CRS(0)
NL21	197.3%	0	84.0261	0	0	CRS(0)
NL22	228.2%	913.284	49.3851	0	0	CRS(0)
NL23	231.2%	0	117.942	0	0	CRS(0)
NL31	192.4%	0	84.0262	0	0	CRS(0)
NL32	189.5%	913.285	49.3852	0	0	CRS(0)
NL33	190.1%	0	117.943	0	0	CRS(0)
NL34	156.6%	0	84.0263	0	0	CRS(0)
NL41	112.0%	913.286	49.3853	0	0	IRS(+)
NL42	180.9%	0	117.944	0	0	CRS(0)
PL11	477.1%	0	84.0264	0	0	IRS(+)
PL12	403.1%	913.287	49.3854	0	0	CRS(0)
PL21	517.6%	0	117.945	0	0	CRS(0)
PL22	429.0%	0	84.0265	0	0	CRS(0)
PL31	709.6%	913.288	49.3855	0	0	CRS(0)
PL32	646.8%	0	117.946	0	0	CRS(0)
PL33	252.7%	0	84.0266	0	0	IRS(+)
PL34	334.1%	913.289	49.3856	0	0	IRS(+)
PL41	449.5%	0	117.947	0	0	CRS(0)
PL42	292.6%	0	84.0267	0	0	IRS(+)
PL43	166.9%	913.290	49.3857	0	0	IRS(+)
PL51	392.0%	0	117.948	0	0	CRS(0)
PL52	171.5%	0	84.0268	0	0	IRS(+)
PL61	340.4%	913.291	49.3858	0	0	IRS(+)
PL62	384.1%	0	117.949	0	0	IRS(+)
PL63	483.3%	0	84.0269	0	0	CRS(0)
PT11	457.9%	913.292	49.3859	0	0	CRS(0)
PT15	219.0%	0	117.950	0	0	IRS(+)
PT16	423.6%	0	84.0270	0	0	CRS(0)
PT17	324.8%	913.293	49.3860	0	0	IRS(+)
PT18	247.3%	0	117.951	0	0	IRS(+)
RO11	501.4%	0	84.0271	0	0	CRS(0)
RO12	261.1%	913.294	49.3861	0	0	CRS(0)
RO21	456.6%	0	117.952	0	0	CRS(0)

RO22	100.0%	N/A	N/A	N/A	N/A	CRS(0)
RO31	529.3%	913.295	49.3862	0	0	IRS(+)
RO32	535.9%	0	117.953	0	0	CRS(0)
RO41	145.4%	0	84.0273	0	0	CRS(0)
RO42	299.1%	913.296	49.3863	0	0	CRS(0)
SE11	110.2%	0	117.954	0	0	IRS(+)
SE12	166.0%	0	84.0274	0	0	IRS(+)
SE21	152.7%	913.297	49.3864	0	0	CRS(0)
SE22	116.2%	0	117.955	0	0	IRS(+)
SE23	183.6%	0	84.0275	0	0	CRS(0)
SE31	148.3%	913.298	49.3865	0	0	CRS(0)
SE32	131.1%	0	117.956	0	0	CRS(0)
SE33	187.4%	0	84.0276	0	0	CRS(0)
SI01	394.8%	913.299	49.3866	0	0	CRS(0)
SI02	365.7%	0	117.957	0	0	CRS(0)
SK01	370.9%	0	84.0277	0	0	CRS(0)
SK02	251.4%	913.300	49.3867	0	0	IRS(+)
SK03	418.1%	0	117.958	0	0	IRS(+)
SK04	413.9%	0	84.0278	0	0	IRS(+)
UKC1	193.2%	913.301	49.3868	0	0	CRS(0)
UKC2	176.0%	0	117.959	0	0	CRS(0)
UKD1	164.4%	0	84.0279	0	0	CRS(0)
UKD3	165.9%	913.302	49.3869	0	0	CRS(0)
UKD4	192.1%	0	117.960	0	0	CRS(0)
UKD6	242.1%	0	84.0280	0	0	CRS(0)
UKD7	201.8%	913.303	49.3870	0	0	CRS(0)
UKE1	174.5%	0	117.961	0	0	CRS(0)
UKE2	201.7%	0	84.0281	0	0	CRS(0)
UKE3	201.9%	913.304	49.3871	0	0	CRS(0)
UKE4	164.6%	0	117.962	0	0	CRS(0)
UKF1	235.2%	0	84.0282	0	0	CRS(0)
UKF2	177.8%	913.305	49.3872	0	0	CRS(0)
UKF3	117.8%	0	117.963	0	0	IRS(+)
UKG1	255.0%	0	84.0283	0	0	CRS(0)
UKG2	162.2%	913.306	49.3873	0	0	CRS(0)
UKG3	175.3%	0	117.964	0	0	CRS(0)
UKH1	224.5%	0	84.0284	0	0	CRS(0)
UKH2	225.8%	913.307	49.3874	0	0	CRS(0)
UKH3	211.7%	0	117.965	0	0	CRS(0)
UKI1	100.0%	N/A	N/A	N/A	N/A	CRS(0)
UKI2	165.6%	913.308	49.3875	0	0	CRS(0)
UKJ1	166.3%	0	117.966	0	0	CRS(0)
UKJ2	162.7%	0	84.0286	0	0	CRS(0)
UKJ3	213.6%	913.309	49.3876	0	0	CRS(0)
UKJ4	223.5%	0	117.967	0	0	CRS(0)
UKK1	191.4%	0	84.0287	0	0	CRS(0)
UKK2	155.3%	913.310	49.3877	0	0	CRS(0)
UKK3	100.0%	N/A	N/A	N/A	N/A	CRS(0)
UKK4	173.5%	0	84.0288	0	0	CRS(0)
UKL1	185.9%	913.311	49.3878	0	0	CRS(0)
UKL2	191.8%	0	117.969	0	0	CRS(0)
UKM2	170.1%	0	84.0289	0	0	CRS(0)
UKM3	207.2%	913.312	49.3879	0	0	CRS(0)
UKM5	161.4%	0	117.970	0	0	CRS(0)
UKM6	181.1%	0	84.0290	0	0	CRS(0)
UKN0	205.0%	913.313	49.3880	0	0	CRS(0)

Source: own work. (N/A – for DMUs with 100% efficiency coefficient no additional changes of inputs and/or outputs are offered)