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The Importance of Implementing Environmental Variables in the Process of Assessment of Healthcare Efficiency through DEA[1]

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Abstract

In this paper, the regional efficiency of healthcare facilities in Slovakia is measured (2008 – 2015) using a Data Envelopment Analysis (DEA). The window DEA was chosen since it leads to increased differentiation of results, especially when applied to small samples, and it enables year-by-year comparisons of the results. Two inputs (number of beds, number of medical staff) and two outputs (use of beds, average nursing time) were chosen as variables in output-oriented 4-year window DEA model for the assessment of technical efficiency in 8 Slovak regions. As the regional efficiency is driven by natural, historical, macro-economic and political conditions, in the next stage the impact of environmental factors on efficiency is examined. The results have confirmed that the public costs, private costs, departments, higher education, population over 65, life expectancy, wage costs, population size and income inequality indicator s80/s20 are statistically significant and therefore affect the efficiency of healthcare facilities in Slovakia.

Keywords: *regional efficiency, data envelopment analysis, window analysis, regression analysis*

JEL Classification: C61, I11, R11, R58

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Introduction

Regional efficiency and possibilities of its improvement have become one of the leading imperatives of all world economies. Achieving balanced national development and reducing interregional disparities is an economic challenge. Regional efficiency is generally assessed by partial comparisons of regional growth and development indicators. The indicator of gross domestic product is mostly compared with other socio-economic indicators. Each of these comparisons gives us information about their correlation but does not give us a complete picture of the achieved level of regional development. Traditional methods of measuring efficiency require knowledge of an exact functional form linking outputs and inputs, or prior determination of inputs and output weights, which makes the assessment of their importance subjective.

The purpose of this paper is to present the results of the analysis of efficiency in Slovakia, extending traditionally used efficiency measuring methods by *Data Envelopment Analysis*. We address two research questions: What was the technical efficiency of regional healthcare facilities in the years 2008 – 2015? How do institutional and environmental variables affect the efficiency of regional healthcare facilities in Slovakia? The specific objectives of our study are: to estimate the technical efficiency of regional healthcare facilities and to determine the impact of institutional and environmental variables on the efficiency of regional healthcare facilities. We use a two-stage DEA model to estimate the efficiency on a regional level and a panel regression model to explain the inefficiency.

We organise the paper as follows. Section 1 discusses the review of the literature dealing with the implementation of the DEA in the healthcare system. Section 2 introduces the methodology which is adopted by the present paper and defines the data used in the analytical part of the paper. Empirical results of the model are presented in section 3, as well as a discussion of the ability of each region to achieve a standard level of economic growth. Finally, in the last section, the main findings of the study are highlighted.

1. Literature Review

From a historical point of view, we consider Farrell as the one who lays down the foundations of the DEA method. In his work (1957), Farrell starts to measure efficiency by assuming that only one input enters the model and produces only one output. Charnes, Cooperr and Rhodes (1978), who extended the original Farrell model, can be considered as authors of the first comprehensive model with multiple variables. The base model created by them is referred to as the CCR model, defined by the assumption of a constant return to scale (CRS). Later, authors Banker, Charnes and Cooper (1984) expanded this model with the assumption of a variable return to scale (VRS), which is known as the BCC model. The assumption of a variable return to scale modifies the efficiency frontier, where a straight line no longer represents the graph, but the shape of the efficiency frontier is convex. The BCC model, compared to the CCR model, identifies multiple production units (DMUs) as efficient, as it allows the existence of imperfect competition. The DMU may represent different levels of health care, including a complete health care system in the country, region, district, hospital, specific services, department, or individual physicians. When applying the DEA method, it is essential to decide on the orientation of the model towards inputs or outputs. Input-oriented models for shifting to the efficiency frontier do not require a change on the output side, but they examine what proportional reduction of inputs is needed to achieve efficiency.

On the other hand, output-oriented models for achieving efficiency frontier look for an answer to the question of what maximum output can be achieved by using a given number of inputs. Both orientations were applied in the healthcare sector. Output-oriented models are preferred by Hernandez and San Sebastian (2014); Oikonomou et al. (2016); Li and Dong (2015); Cheng et al. (2016); Mujasi, Asbu and Puig-Junoy (2016); Mahate, Hamidi and Akinci (2016). Input-oriented models are used by Czypionka et al. (2014), and Fragkiadakis et al. (2016). Views on the selection of a suitable model, its application and convenience vary. Hernandez and San Sebastian (2014) argue that in the case of primary and secondary healthcare provision, inputs are uniform and low in numbers, and health outcomes could be increased to achieve improved health promotion. They also express the view that in many cases the need for health services is insufficiently met. In such situations, it would be unethical to reduce the amount of healthcare provided to improve hospital efficiency. Cheng et al. (2016) justify the choice of an output-oriented model due to limited control of hospital managers over their inputs and due to controlled decisions on recruitment and investments by government departments. Oikonomou et al. (2016) justify the choice of an output-oriented model by the fact that the demand for primary healthcare services tends to expand and not decrease. Furthermore, they believe that reducing inputs in the provision of health services is undesirable, while increasing outputs is feasible.

The second important step in the DEA analysis is the choice of input and output variables. Input variables represent the inputs of the transformation process in generating health outcomes. These are controllable variables which directly affect the health services provided by a hospital. One of the most commonly used indicators on the input side for comparing hospitals within European countries is the number of beds. We can find this variable at the national level in the studies of Kooreman (1994); Gerdtham et al. (1999), and Maniadakis and Thanassoulis (2000). Several authors have used the number of beds variable for international comparison (Varabyova and Schreyögg, 2013; Samut and Cafri, 2015). The second most frequently used input variable is the number of employees (Lacko et al., 2014). In Baray and Cliquet (2013), and Maestre, Oliveira and Barbosa-Póvoa (2015), the total number of employees, without subdivision of employees into subgroups, is tracked as the primary indicator. According to these authors, the total number of employees is the primary indicator needed to monitor economic outturn. It shows the size of the hospital and the potential which the hospital facility can offer to patients. The indicator also corresponds with the size of the catchment area of patients, who according to the geographical location of the hospitalise the particular hospital (Maestre, Oliveira and Barbosa-Póvoa, 2015). Tracking the number of employees alone has no informative value. Of course, the number of employees significantly affects the increase in wage costs with each additional employee (Baray and Cliquet, 2013). It is up for a discussion as specific categories of employees are more critical than the others and what total numbers of all employees are optimal. Kooreman (1994); Maniadakis and Thanassoulis (2000); Varabyova and Schreyögg (2013), and Li and Dong (2015) used the total number of employees as an input into the efficiency assessment models. The total number of medical staff, other technical staff, and the number of non-medical staff were studied as an input variable by Cheng et al. (2016). Czypionka et al. (2014) used the medical and non-medical staff as an input variable, Mahate, Hamidi and Akinci (2016) divided the input variables for doctors, dentists, nurses, pharmacists, administrative and other workers, Fragkiadakis et al. (2016) used inputs like clinical staff, nurses and administrative staff.

Output variables are a measurable expression of the provided healthcare services. The ideal indicator of healthcare output would be the level of health gained by individual patients, but this is not easily measurable and reportable. Therefore, we use variables which are measurable and reportable. In the literature, we often meet the use of beds variable (Kooreman, 1994; Chang and Lan, 2010; Perera, Dowell and Crampton, 2012; Belciug and Gorunescu, 2015; Dy et al., 2015). The use of bed indicator generally refers to the percentage utilisation of the total number of hospital beds for a specified period, typically a calendar year (Belciug and Gorunescu, 2015). As reported by Dy et al. (2015), this indicator directly reflects the use of resources available to the hospital.

It shows whether the hospital efficiently manages the use of its capacities, whether it has enough free beds and whether it can meet the demand of patients on time and to a sufficient extent. Low use of bed is a warning signal of inefficient use of financial resources and hospital capacities, which should lead to a reduction in the number of beds with the unchanged satisfaction of patients while reducing the costs of bed operation and maintenance (Perera, Dowel and Crampton, 2012).

The second frequently used output variable is the average treatment time. The indicator of average treatment time tells us the length of the patient’s stay on the bed in the facility. If the average treatment time were shortened, the total costs would be reduced as the costs of the patient´s treatment on the bed would be reduced. Also, the trend of lower-cost outpatient treatment used in even more complicated cases adds to the reduction of costs. The average treatment time in day variable was used by authors Kooreman (1994), Chang and Lan (2010), Varabyova and Schreyögg (2013) in DEA research of efficiency.

Recently, we have been studying the studies of authors focused on the impact of external (or environmental) factors on the effectiveness of healthcare (Chang and Lan, 2010; Ramirez-Valdivia, Maturana and Salvo-Garrido, 2011; Varabyova and Schreyögg, 2013; Mitropoulos, Mitropoulos and Sissouras, 2013; Samut and Cafri, 2015; Chowdhury and Zelenyuk, 2016; Mujasi, Asbu and Puig-Junoy, 2016; Fragkiadakis et al., 2016). Environmental variables are variables which a hospital or health facility is incapable of influencing but may affect the effectiveness of the hospital positively or negatively. These variables are not directly input or output of the health facility. They are most commonly referred to as external factors. These variables are also included in the social, socioeconomic or demographic categories (Mura and Orlíková, 2016). Demographic factors are used by authors Retzlaff-Roberts, Chang and Rubin (2004); Ramirez-Valdivia, Maturana and Salvo-Garrido (2011); Fragkiadakis et al. (2016). The most frequently used external variables are: health sector costs (Chang and Lan, 2010; Ramirez-Valdivia, Maturana and Salvo-Garrido, 2011; Varabyova and Schreyögg, 2013; Samut and Cafri, 2015), income inequality (Retzlaff-Roberts, Chang and Rubin, 2004; Ramirez-Valdivia, Maturana and Salvo-Garrido, 2011; Varabyova and Schreyögg, 2013), population over 65 years (Chang and Lan, 2010; Ramirez-Valdivia, Maturana and Salvo-Garrido, 2011; Varabyova and Schreyögg, 2013), life expectancy (Varabyova and Schreyögg, 2013; Samut and Cafri, 2015), infant mortality (Varabyova and Schreyögg, 2013), mortality rate (Mitropoulos, Kounetas and Mitropoulos, 2016), employment rate (Varabyova and Schreyögg, 2013; Fragkiadakis et al., 2016), costs in the organization (Varabyova and Schreyögg, 2013; Samut and Cafri, 2015), population size (Mujasi, Asbu and Puig-Junoy, 2016), population density (Ramirez-Valdivia, Maturana and Salvo-Garrido, 2011; Fragkiadakis et al., 2016), geographical location (Mitropoulos, Mitropoulos and Sissouras, 2013; Chowdhury and Zelenyuk, 2016), density of hospitals (Varabyova and Schreyögg, 2013), GDP (Samut and Cafri, 2015), and income inequality (Retzlaff-Roberts, Chang and Rubin, 2004, Ramirez--Valdivia, Maturana and Salvo-Garrido, 2011; Varabyova and Schreyögg, 2013).

2. Methodology and Data Used

In order to evaluate the technical efficiency of a healthcare system of the Slovak Republic at the regional level, we decided to apply the output-oriented models, CCR and BCC, based on the DEA window analysis. Output oriented CCR model can be formulated in the matrix form by the following formula:

Maximise $$g = \phi_q + \varepsilon(e^T s^+ + e^T s^-) \tag{1}$$

Under conditions
$$X\lambda + s^- = x_q$$
$$Y\lambda - s^+ = \phi_q y_q$$
$$\lambda, s^+, s^- \geq 0$$

where

- ε – constant,
- q – evaluated DMU,
- y_q – the output of evaluated DMU*q*,
- x_q – input of evaluated DMU*q*,
- s^+ and s^- – slack variables for inputs and outputs.

As stated by Jablonský and Dlouhý (2004), based on the model (1), the production unit is evaluated as efficient if the optimal value of the function $g^* = 1$ and all complementary variables are equal to zero. If this value is above 1, the DMU cannot be considered as efficient, and the optimal value ϕ_q^* expresses the need for a proportional increase in inputs to achieve efficiency. Assuming that production units operate under the variable return to scale (increasing, decreasing, non-increasing, non-decreasing), we apply the BCC output-oriented model, into which we add a convexity condition $e^T\lambda = 1$.

When evaluating efficiency, we can sometimes encounter a limited number of DMUs. When we want to overcome this problem, we can apply a DEA window analysis. It allows us to compare the efficiency of a limited number of DMUs in specific periods and to analyse efficiency changes over time. The DEA window analysis generalises the idea of moving averages to detect the trend of DMU efficiency development over time. The moving average method is used to compile a different sample to determine the relative efficiency of each DMU. Based on the dynamic perspective, each DMU is considered as a separate unit in specific periods in individual windows (Cooper, Seiford and Tone, 2007). The input and output variables of the DMU in the selected period are compared to those of other DMUs in all periods. We also compare the results of the DMU from one period with the results of the same unit in the remaining periods. When the window moves for the first time, at the same time the first period is deleted in each window and a new period is added. The benefit of this method is a comprehensive description of dynamic changes in the efficiency of each DMU, both horizontal and vertical. Of course, the main benefit is an increase in the number of DMUs, which raises the discriminatory power in situations with a limited number of DMUs in the sample (Jia and Yuan, 2017). In Slovakia, the issue of healthcare and the application of the DEA window analysis method were dealt with by Sendek, Svitálková and Angelovičová (2015), who focused on assessing the efficiency of hospitals in the Czech and Slovak Republics using the BCC model.

We assume a sample of N (n = 1, ..., N) DMUs during T (t = 1, ..., T) periods. Each DMU uses r different inputs to produce s different outputs. If DMU_n^t is a combination of inputs and outputs for the N^{th} unit of the DMU in the T period, then the input vector X_n^t and output vector Y_n^t can be written as follows:

$$X_n^t = \begin{bmatrix} x_n^{1t} \\ \vdots \\ x_n^{rt} \end{bmatrix} Y_n^t = \begin{bmatrix} y_n^{1t} \\ \vdots \\ y_n^{st} \end{bmatrix} \tag{2}$$

If the window starts in time k ($1 \le k \le T$) and the width of the window is w ($1 \le k \le T\text{-}k$), then the input matrix (X_k^w) and the output matrix (Y_k^w) of each window will be as follows:

$$X_k^w = \begin{bmatrix} x_1^k & x_2^k & \cdots & x_N^k \\ \vdots & \vdots & \ddots & \vdots \\ x_1^{k+w} & x_2^{k+w} & \cdots & x_N^{k+w} \end{bmatrix} Y_k^w = \begin{bmatrix} y_1^k & y_2^k & \cdots & y_N^k \\ \vdots & \vdots & \ddots & \vdots \\ y_1^{k+w} & y_2^{k+w} & \cdots & y_N^{k+w} \end{bmatrix} \tag{3}$$

The input-oriented CCR window model can be defined as follows:

$$\max \eta \tag{4}$$

Subject to:

$$X_t - \lambda X_{kw} \ge 0$$

$$\lambda \mathrm{Y}_{\mathrm{kw}} - \eta \mathrm{Y}_{\mathrm{t}} \ge 0$$

$$\lambda_n \ge 0, (n = 1,\ 2,\ \ldots,\ N \times w)$$

The output-oriented BCC window model can be obtained by adding the condition $\sum_{n=1}^{N\times w}\lambda_n = 1$ (Banker, Charnes and Cooper, 1984).

We will analyse the healthcare system of Slovakia. We have decided to monitor the DMU at the regional level as the best comparable lowest level of tracking. The smaller division into districts was not taken into account due to lack of microdata availability at the relevant level. The indicators monitored by multinational organisations are used as the lowest regional level of NUTS 3, which when applied to Slovakia means the division into regions. In Slovakia, we have a total of eight regions. To evaluate the technical efficiency of healthcare facilities at the level of the Slovak Republic, we used the extended output--oriented CCR models as well as the BCC model of DEA window analysis. By literature study, we have chosen to use the output-oriented model, since, in the field of healthcare, human health is the primary objective. When it comes to the issue of healthcare efficiency, it is essential to focus attention on the quality of provided services, on the quantity and satisfaction of patients, and also to focus on increasing patient satisfaction due to a better and higher-quality healthcare system. It will result in more treatments, more procedures, more hospitalisations, more releases, and the resulting increase in quality of life and health, decreasing mortality rates due to late diagnosis and inadequate treatment. From the moral point of view, the healthcare system is specific, and the aim of hospitals and healthcare facilities should not be to reduce inputs and costs but rather to concentrate on increasing outputs in the form of abovementioned objectives. Therefore, we prefer to use an output-oriented DEA model. We used the data from the databases of the National Health Information Center, Statistical Office of the Slovak Republic, online databases Slovstat and DataCube, the OECD databases and the databases of the European Statistical Office EUROSTAT. The input and output variables have been compiled from a detailed analysis and research of the most commonly used variables in published literature. The rules for the construction of the DEA models and limitations for sample size determination were also taken into account. The number of beds (x1) and the number of medical staff (x2) were chosen as input variables in our analysis. Since the primary objective of a hospital is patient care, the use of beds in days (y1), and the average treatment time in days (y2) were chosen as variable health outcomes in our study. The number of beds is an indicator reflecting the size of the hospital. It is clear from this indicator that each added bed means an extra cost for the hospital for its provision and operation. The operation is related to the marginal wage costs needed by staff who have to take care of each patient as well as other costs associated with complementary products (e.g. bedding). On the other hand, the beds mean the possibility of providing essential hospital services, thus bringing the marginal profit to the hospital. Whether directly from the patient or from a health insurance company which reimburses hospitals for payments made for medications, and other medical supplies. The number of the medical staff represents the registered number of employees – natural persons, being the sum of the number of doctors, dentists, pharmacists, nurses, midwives, lab technicians, assistants, technicians and other medical staff. The data was collected for variables during the reference period of 2008 – 2015. The summary statistic is shown in Table 1.

Table 1

Summary Descriptive Statistics of Variables in Calculating Efficiency Using DEA

		x1	**x2**	**y1**	**y2**
2015	Minimum	2 437	6 022	221	7
	Maximum	5 381	17 299	263	9
	Average	3 934	10 040	244	8
	Median	3 945	9 264	249	8
2014	Minimum	2 408	6 202	218	7
	Maximum	5 554	17 248	267	8
	Average	3 952	9 966	245	8
	Median	3 934	8 995	248	8
2013	Minimum	2 373	6 134	223	7
	Maximum	5 563	17 054	264	8
	Average	3 954	9 933	245	8
	Median	3 956	8 787	251	8
2012	Minimum	2 348	6 120	224	7
	Maximum	5 356	17 127	268	8
	Average	4 030	9 904	246	8
	Median	3 931	9 056	249	8
2011	Minimum	2 533	6 246	214	7
	Maximum	5 736	17 163	263	9
	Average	4 119	9 855	237	8
	Median	3 954	8 790	242	8
2010	Minimum	2 637	6 424	215	7
	Maximum	5 934	16 472	258	9
	Average	4 392	9 944	238	8
	Median	4 233	9 040	243	8
2009	Minimum	2 568	6 483	217	7
	Maximum	5 988	16 031	251	9
	Average	4 440	9 745	238	8
	Median	4 326	8 977	241	9
2008	Minimum	2 558	6 513	221	8
	Maximum	5 930	15 405	251	9
	Average	4 460	9 892	239	8
	Median	4 285	9 539	242	9
2008 – 2015	Minimum	2 348	6 022	214	7
	Maximum	5 988	17 299	268	9
	Average	4 162	9 898	242	8
	Median	4 078	9 475	244	8

Explanatory notes: x1 – the number of beds in pieces; x2 – the number of medical staff in persons; y1 – use of beds in days; y2 – average nursing time in days.

Source: Own calculations in the program MsExcel.

From the descriptive statistics, we can see that the difference between the minimum and the maximum is approximately up to two times in each year of the monitored period for the number of beds in pieces variable. It suggests that the size of the regional distribution is significant and the results in regions are different up to two times when comparing the minimum and maximum values in the sample. A similar but even more pronounced difference across regions is seen in the number of medical staff variable, where the maximum for the whole analysed period is up to 2.87 times higher than the minimum. Numerically, the most significant differences are in the Bratislava and Trnava regions. In the Bratislava region in 2015, the total number of medical staff was 17 299 compared to the Trnava region where the number of medical staff was only 6 022 persons.

The „use of beds in days" variable is less differentiated across the region compared to the previous two. The difference in the total period in days between the maximum and the minimum is only 1.25 times. The average minimum bed occupancy in days during the period 2008 – 2015 is 242 days per year, with a minimum of 214 and a maximum of 268 days. The most productive was the Nitriansky region in 2012 with a total of 268.4 days of bed use per year. The Trnava region achieved the worst result of only 214.0 days of use of beds per year in 2011. The average daily treatment time across all regions during the whole analysed period declined, so the regions reduced the treatment time in the period from 2008 to 2015. The highest average treatment time was in the Košice region in 2008 and Nitriansky region in two consecutive years – 2009 and 2010. The shortest nursing time was 6.8 days in the Trnava region in 2014 and 2015.

Regarding the median values of individual variables in the monitored period, the following situations occurred: the number of beds decreased by 8% from 4285 to 3945; the number of medical staff declined by 3% from 9539 to 9264; the use of beds in days increased by 3% from 242 to 249 days; average nursing time in days decreased by 11% from 9 to 8.

In the second step, we estimate the impact of environmental, i.e. external factors beyond the management of healthcare facilities on the efficiency estimated by the DEA window analysis within the first step. We assume that there are factors that significantly affect efficiency but are not directly influenced by management. The selection of suitable variables was made after the study of relevant literature.

A summary of all environmental variables that have been selected as explanatory variables in the regression analysis by the study of relevant literature is shown in Table 2.

T a b l e 2

Specification of Environmental Variables

Environmental variables	**Definition**
Public sector costs	Cost per unit of healthcare per person in USD
Costs of the private sector	The ratio of the cost of the private sector to total healthcare costs
Departments	Sum of all types and subcategories of healthcare facilities
Higher education	Number of the economically active population with achieved second level of education
Population over 65 years	Population aged over 65
Life expectancy	Life expectancy at birth
Infant mortality	Mortality of live births up to 1 year of life
Employment	Number of workers per year in the country in thousands
Costs together	Total costs of the healthcare organisation
Wage costs	Cost of the healthcare organisation for wages
Cost of Medical Devices	Costs of the healthcare organisation for medical devices
Revenue together	Total revenues of the healthcare organisation
Average population	Average population in thousands
GDP	Gross domestic product at constant prices (EUR million, EUR per capita, EUR per capita as a percentage of EU average, PPS per capita, PPS per capita, PPS per inhabitant as a percentage of EU average)
The uncertainty of income distribution s80/s20	The ratio of 20% of the population with the highest income to 20% of the population with the lowest income

Source: Prepared by authors.

3. Results of the Analysis

Estimated efficiency for the years 2008 – 2015 using the DEA model analysis, assuming a constant return to scale (CCR model), is expressed in the following table (Table 3). We can see that the regions of Trnava, Trenčín, Nitra and Banská Bystrica are above-average in efficiency throughout the analysed period. Below the average is the Žilina, Bratislava, Prešov and Košice regions. Efficiency at 1 (or 100%) according to the CCR model was reached by the Trnava region in 2008, 2011, 2012 and 2015, Trenčín region in 2011, 2012 and 2015, and Nitra region in 2009.

T a b l e 3

Estimation of the Efficiency of the CCR Model in 2008 – 2015

CCR_O	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2008 – 2015**	**Change (%)**
Bratislava	0.5462	0.5458	0.5415	0.5767	0.5718	0.5846	0.5751	0.5663	0.5635	3.68
Trnava	1	0.9840	0.9832	1	1	0.9953	0.9810	1	0.9929	0.00
Trenčín	0.9677	0.9760	0.9808	1	1	0.9977	0.9964	1	0.9898	3.33
Nitra	0.9132	1	0.9609	0.9280	0.9294	0.9378	0.9522	0.9203	0.9427	0.77
Žilina	0.7403	0.7171	0.6888	0.6990	0.6767	0.7031	0.6852	0.6603	0.6963	–10.80
Banská Bystrica	0.7863	0.8717	0.8752	0.8595	0.8529	0.8893	0.8695	0.8314	0.8545	5.73
Prešov	0.6919	0.7201	0.6534	0.6715	0.6520	0.6672	0.6374	0.6276	0.6651	–9.29
Košice	0.5833	0.5394	0.5206	0.5255	0.5256	0.5115	0.5008	0.5032	0.5262	–13.74
Average	0.7786	0.7943	0.7755	0.7825	0.7760	0.7858	0.7747	0.7636	0.7789	–1.93

Source: Own calculations.

The best average values were reached in the Trnava region, with no significant deviations in the achieved efficiency over the monitored period. On the contrary, the Košice region achieved the most significant change, up to 13.74% decrease in the average efficiency achieved between the year 2008 and 2015. Other regions with declined efficiency were the Žilina region and the Prešov region by 10.80% and 9.29%, respectively. The most significant increase was reached by the Banská Bystrica region, 5.73%.

In the following table (Table 4), we can see the evolution of the estimated efficiency of the DEA model assuming a variable return to scale (BCC model). The BCC model compared to the CCR model reached higher average values of estimated efficiency, which is in line with the defined assumptions. The Trenčín, Trnava and Nitra regions have again reached above-average values throughout the analysed period. According to the model, the Banská Bystrica, Žilina and Prešov regions are below the average. The region of Košice recorded the most significant decline. The Bratislava, Žilina, Banská Bystrica, and Prešov regions also declined. On the contrary, the Trenčín and Nitra regions were growing, with the highest growth in the Trenčín region.

T a b l e 4

Estimation of the Efficiency of the BCC Model in 2008 – 2015

BCC_O	2008	2009	2010	2011	2012	2013	2014	2015	2008 – 2015	Change (%)
Bratislava	0.9667	0.9556	0.9333	0.9505	0.9746	0.9848	0.9706	0.9579	0.9618	–0.91
Trnava	1	0.9914	0.9904	1	1	0.9958	0.9860	1	0.9955	0.00
Trenčín	0.9712	0.9809	0.9854	1	1	1	1	1	0.9922	2.97
Nitra	0.9889	1	1	1	1	0.9978	1	1	0.9983	1.12
Žilina	0.9529	0.9427	0.9268	0.9121	0.9299	0.9314	0.9378	0.9266	0.9325	–2.75
Banská Bystrica	0.9667	0.9556	0.9541	0.9236	0.9451	0.9593	0.9497	0.9467	0.9501	–2.06
Prešov	0.9556	0.9444	0.9000	0.8992	0.8953	0.9201	0.9006	0.8941	0.9137	–6.43
Košice	1	0.9679	0.9493	0.9433	0.9601	0.9476	0.9357	0.9385	0.9553	–6.15
Average	0.9752	0.9673	0.9549	0.9536	0.9631	0.9671	0.9601	0.9580	0.9624	–1.77

Source: Own calculations.

After performing efficiency estimates using the CCR and BCC models and partial analyses of each of them, we can conclude that both models created by us produce very similar results, no model has estimated an extreme value. In both models, the Trenčín, Trnava and Nitra regions were above the average. When we look at the development of time variables, the above-average values were reached repeatedly by different regions. The highest values in the x1 variable were reached in regions of Bratislava, Košice and Žilina. For variable x2, the highest values were reached in the region of Bratislava and Košice. For the y1 variable, the highest values were reached by regions of Žilina, Košice, Bratislava, Prešov and Banská Bystrica. For a y2 variable, the highest values were reached by regions of Bratislava, Žilina, Prešov and Banská Bystrica. We can see that Trenčín, Trnava and Nitra are not above the average in any input or output variables. Therefore, when assessing efficiency, it is essential to ensure that satisfactory outcomes (use of beds and average care hours) can be provided with a given number of input variables (number of beds and the number of healthcare workers). In a more in-depth analysis and comparison of the „number of beds" and the „use of beds", we can see that the regions with the highest number of beds use are less efficient than regions with fewer beds. We can suppose that these regions had surpluses of beds compared to their usage. When looking at the ratio of the number of medical staff to the second observed variable - average outpatient treatment time, we obtain similar results as in the previous situation. The same result is obtained by proportional variations in the number of medical staff in the variable use of beds. Recommendations based on the performance analysis are for the Bratislava, Košice, Žilina and Prešov regions in terms of output orientations for increasing the use of beds and treatment time with unchanged bed counts and number of health workers. This outcome is debatable, since the increase in the average treatment time may mean the implementation of more difficult treatment procedures, hospitalisation of which is demanding; which is desirable in terms of demand for healthcare services. There is, however, a trend to reduce the average length of treatment due to the shift of hospitalised outpatient services and saving of beds and working time of medical staff. Excessive reductions in average nursing time may lead to re-hospitalisations and re-operations, which would reduce efficiency.

In the second step, we monitored the impact of environmental, external variables on the efficiency estimated by the CCR and BCC models in the previous section. Medical devices can only influence internal variables – variables that are variable at the level of management of individual healthcare facilities. In this section, our goal is to monitor factors which cannot be influenced by the management of healthcare facilities, but we assume that there is a link between the environmental specificities of the region, catchment area populations or other macro-economic factors and efficiency. We assume that healthcare facilities can only partially affect overall efficiency, as there are factors which have a greater or lesser impact on service performance and thus the overall efficiency of healthcare facilities. It is interesting to look at their impact and find a formula that determines whether the selected variables affect efficiency and, if so, whether positively or negatively. For this purpose, regression analysis should be used.

Regression analysis is a statistical tool with a wide range of uses. For our needs, we used three types of modelling in the R program, which are explained by Croissant and Millo (2008). These are „pooling" „random" and „within" models. The pooling model is independent of random and fixed effects; the random model captures random effects, and the within model captures the impact of fixed effects (Croissant and Millo, 2008). All of the abovementioned environmental variables enter each model as input variables. Any variable which is not significant is excluded from the model based on the general instructions for correct calculation from the model, and in the next test, the model is calculated anew. The procedure is repeated until all variables in the model are statistically significant (Sen and Srivastava, 2012). In the analysis, we use the terms constant and non-constant model, as in the „pooling“ and „random“ models, there is an option to add or not to add (intercept) a constant. Next, we differentiate between the terms „pre-final“ and „final“ in the specification of models. The final model is the abovementioned final model after removing all the variables which are not statistically significant. Since the value of variable acceptability differs in theoretical levels of different authors, we have chosen to use the term „prefinal“ models if a variable *p*-value of which was just above the acceptability limit, and therefore it is interesting to note these variables as well.

Using regression analysis, we determine whether there is a dependency between the dependent (explained) variable and the independent (explanatory) variables. The dependent variable is the efficiency estimated by the DEA analysis. In the DEA analysis, we determined that it is not decidedly more convenient to use either the BCC or the CCR model. In order to select a suitable model, we decided to compare the R squared indicator of all models. According to Wooldridge (2015): the R squared value, also referred to as the coefficient of determination, expresses how well the model explains the observed results. Greene (2012) states that the use of the R squared indicator has limitations, but it is a useful method for selecting a suitable regression analysis model. The value should be in the range of 0.85 to 1. If the value is less than 0.7 the results are insufficiently explained by the model (Wooldridge, 2015). Only a single „within“ model does not explain the results adequately according to the R squared indicator, using both the CCR model and the BCC model data.

The BCC pooling without a constant (pre-final), the BCC pooling without a constant (final), the BCC random without a constant (final), the BCC random with a constant (pre-final) and the BCC random with a constant (final) models do not fall into the ideal set where the R squared value should be found according to Wooldrige (2015) and therefore we cannot say that the results are adequately explained by the models. To select one best model, we compare all the models to each other and choose the model that best explains the variables. The best model based on the statistical value of R squared is the CCR pooling model with a constant (pre-final) of 0.94262, which means that the CCR pooling model explains 94% of variables with a constant (pre-final), and thus approximately 6% is unexplained variability or the influence of random factors and other unspecified influences. Exact results of the R squared are displayed in a table (Table 5) also for other models. The results of the best model are displayed in the next Table (Table 6). The Table shows „Estimate," „Pr(>|t|)" and „Significant Code". Pr(>|t|) represents a p-value which tells us whether a given variable is statistically significant (Wooldridge, 2015).

Table 5

The R Squared of All Models

Model	R Squared	R Squared	Model
CCR pooling without a constant (pre-final)	**0.94156**	**0.83883**	BCC pooling without a constant (pre-final)
CCR pooling without a constant (final)	**0.93877**	**0,83118**	BCC pooling without a constant (final)
CCR pooling with a constant (pre-final)	**0.94262**	**0.87287**	BCC pooling with a constant (pre-final)
CCR pooling with a constant (final)	**0.93992**	**0,86754**	BCC pooling with a constant (final)
CCR random without a constant (pre-final)	**0.93050**	**0.81352**	BCC random without a constant (final)
CCR random without a constant (final)	**0.93313**	**0.82281**	BCC random with a constant (pre-final)
CCR random with a constant (pre-final)	**0.92183**	**0.83153**	BCC random with a constant (final)
CCR random with a constant (final)	**0.93313**	**0.66459**	BCC within
CCR within	**0.24901**		

Source: Own calculations.

Table 6

Regression Analysis of the Best Model Output from the R Program

	Estimate	Std. error	t-value	Pr(>|t|)	
(Intercept)	–1.3843e+00	9.8416e-01	–1.4066	0.1653960	
Public sector costs	–2.3785e-03	9.1370e-04	–2.6031	0.0119547	*
Costs of the private sector	3.7088e-02	2.3480e-02	1.96	0.1201507	
Departments	–1.1362e-03	3.7773e-04	–3.0080	0.0040169	**
Higher education	–3.1738e-03	7.9913e-04	–3.9715	0.0002167	***
Population over 65 years	9.1922e-06	1.3434e-06	6.23	8.092e-09	***
Life expectancy	3.3848e-02	1.2794e-02	2.57	0.0107052	*
Wage costs	–2.7973e-09	6.8269e-10	–4.0974	0.0001439	***
Revenue together	4.6424e-10	1.4437e-10	3.56	0.0022192	**
Average population	–8.0586e-04	3.0623e-04	–2.6316	0.0111070	*
S80/S20	3.4844e-02	1.8174e-02	1.72	0.0606120	.
Total Sum of Squares: 2.0547					
Residual Sum of Squares: 0.1179					
R-Squared: 0.94262					
Adj. R-Squared: 0.9318					
F-statistic: 87.0689 on 10 and 53 DF, p-value: < 2.22e-16					

Explanatory notes: Estimate – the correlation coefficient shows the estimate of the dependence between the efficiency and the specific variable, Pr(>|t|) – P-value indicates whether the given variable is statistically significant at a given confidence interval, Std. Error – Medium value error, Signif. Codes – 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ''.

Source: Own calculations.

The significant code is a sign to determine the confidence interval within which a change in the relationship between a dependent variable and an independent variable occurs. The sign at the coefficient denotes the positive value of direct dependence and vice versa in the negative value of indirect dependence between the efficiency and the specific environmental variable (Sen and Srivastava, 2012). Based on the model, nine variables were determined as statistically significant, and one variable is determined by the model to be statistically significant at the 82% confidence interval, which is a very close but high value which will also be interpreted.

The model determined that there is a negative impact on public sector costs on the overall efficiency of medical devices. The same results are presented by Samut and Cafri (2015). By input data, we can say that the amount of public sector health care costs on total healthcare costs during the reference period ranged from 90% in 2008 to 80% in 2015. The trend in the share of public expenditure is a gradual decline which indicates the increasing share of the private sector in the financing of health care. The share of public spending far exceeds private costs. The negative impact of public spending may be caused by the fact that the resources redistributed at the state level in the form of governmental decision do not follow the fair use of distributed resources and; therefore, their use may not be efficient. An interesting result is the adverse outcome of the private sector healthcare costs, which is estimated by the model to be positive. It is, therefore, more efficient if the share of financing by the private sector increases compared to public health costs. It is likely that spending from the private sector is more closely monitored and more emphasis is placed on controlling the use of these funds. Similar, public resources are distributed from a central point without direct contact and knowledge of the particular situation and needs of the given healthcare facility, its current situation, competition, environment, geography, demography or other regional macro-economic indicators. We expect private sector funding to be more useful, as resource use is based on real needs and funding flows to the health sector at times and for purposes that reflect appropriate demands in the regions. Based on the outcome of the first two variables, the recommendation and conclusion on how to increase the efficiency of healthcare facilities are to increase the share of healthcare costs from the private sector.

The growing number of departments has a negative impact on the efficiency of healthcare facilities. The various departments deal with a narrowly specialised field of medicine. Our analysis has shown that allocation to specific departments has an impact on efficiency, but this effect is adverse. Therefore, it is essential to consider whether a distribution to really small, narrowly specialised departments is effective for hospitals and other healthcare facilities. New small departments bring with them requirements for a place for performance, i.e. an outpatient department or a whole department. It is related to the cost of procurement of new premises, or the extension or refurbishment of existing premises, according to new requirements for separate premises for each separate department. In addition to these costs, it is necessary not to forget about the equipment and, last but not least, the costs of doctors and nurses and other medical and non-medical staff. It is questionable whether excessive specialisation is not a significant financial burden on both entry and operating costs. Of course, it is crucial for the quality of the services provided that individual operations are carried out by specialists on the issue, but excessive division can, as we have proved, lead to inefficiency. Linking multiple departments into one or the use of the same premises by multiple doctors at different times is a design solution and a possible improvement of the situation with a high number of separate departments and the associated inefficiency of medical facilities. The cost of providing equipment and standard office supplies for ambulances would be saved in the proposed use of the premises, and would not result in not meeting the requirements of specialised services. Approaches to possible solutions to reduce the number of units needed to be careful and only technically similar departments that need similar environment and technology to perform their services should be merged. Reducing the number of departments must not be at the expense of quality and the different types of specialist services. It is necessary to deeply analyse those departments which can be combined to reduce operational and entry costs. Such analysis needs to be carried out at the level of each department in each hospital and health facility separately.

An interesting result has been found in examining the impact of the higher education population on efficiency. This finding contradicts the results of the studies by Varabyova and Schreyögg (2013), and Samut and Cafri (2015). Slovakia, like many other Eastern European countries, has been experiencing a recent phenomenon called the brain drain. It is a trend that highly specialised experts do not find employment on the territory of the Slovak Republic and are forced to leave abroad for work. We assume that one of the reasons why, despite the growing number of university-educated people, the efficiency of healthcare facilities is decreasing is their migration abroad. The second reason may be the drop in the quality of university graduates in the most recent period, the lowering of the requirements for study admission, as well as graduation with the increasing number of people over 65, the efficiency of healthcare facilities increases. The reason may be that the relationship between efficiency and the older population is very closely interconnected. The increasing number of people aged 65 and over is a reflection of the quality of healthcare services and thus directly reflecting the efficiency of healthcare facilities.

Increasing life expectancy at birth is also a reflection of medical facility efficiency. Life expectancy, improving quality of life and providing health services at a level that allows people to live longer and in better health is an excellent indicator of health services efficiency. The goal of an efficient healthcare system is to improve the quality of life and ensure a long and healthy life as possible. Quality diagnostics, prevention and treatment in the early stages of illness significantly increase the probability of successful treatment and, in many cases save human life. Our results are consistent with the results of Varabyova and Schreyögg (2013), and Mitropoulos, Mitropoulos and Sissouras (2013) but in contrast with the results of studies by Chang and Lan (2010). The wage costs of healthcare facilities are statistically significant and have an impact on efficiency. Their impact is negative, which means that with increased wage costs, the efficiency of healthcare facilities is decreasing. The reason could be that with increasing labour cost, the hospitals prefer to reduce the number of nurses and doctors, which could have a negative impact on average nursing time and thus reduce efficiency. Revenues from healthcare facilities have a positive impact on the efficiency of healthcare facilities.

Hospital revenues can be used for staff remuneration increasing the motivation and resulting in improved work commitment and thus the efficiency of work. Hospital proceeds can be used to buy new equipment which can diagnose or treat patients more effectively. Part of the proceeds may also be used for renewal and repairment of existing equipment and devices, condition and functionality of which are necessary for the provision of high-level services. The size of the population has an adverse effect on the efficiency of medical facilities. The same result was obtained by Ramirez-Valdivia, Maturana and Salvo-Garrido (2011); Mitropoulos, Kounetas and Mitropoulos (2016), and Fragkiadakis et al. (2016). The size of the population as an absolute figure represents the nominal population growth. If there is an increase in population with unchanged entries and outputs of hospitals and healthcare facilities, the demand for healthcare services is increasing. If they do not respond to increased demand, they can not meet the demands of the population. At the same time, a large number of population in the hospital catchment area is more likely to experience problematic patients with severe injuries, complicatedly curable diseases, and the like. A large number of population brings a wide range of demanded services and demands different ways and approaches. The more individual patients, the more they bring individual requirements and individual solutions to their problems. It is essential, in particular, for healthcare facilities with a large catchment area, to adequately address the potential demands of patients, to respond flexibly to the demand, and to manage both human and technological resources as efficiently as possible.

Conclusion

In our study, we applied the DEA method to assess the efficiency of the healthcare system in Slovakia. By studying relevant literature, we have found that this method has several advantages and disadvantages. Its advantages influence the frequent use of the DEA method: the DEA allows simultaneous use of multiple inputs and outputs, it does not require a mathematical specification of production function, it is unrelated to standard data partitioning, it is the most appropriate method for the use of exogenous variables, it provides target inputs and outputs for inefficient units to achieve efficiency, and it shows an efficient unit, which helps the inefficient unit to mimic the structure of inputs and outputs. Of course, with the advantages always come the disadvantages as well. The main disadvantages and limitations of DEA are: the results are sensitive to the choice of inputs and outputs, as well as the number of inputs and outputs, and measurement errors and measurement deviations, it provides information about relative efficiency, it is a comparative method which provides information on the DMU efficiency with respect to the DMU sample based on the data input, and the efficiency can not be compared with „ideal standard“, the covariance model the method is known as deterministic and does not have statistical bases, the DEA separability, which states that environmental (external) factors affect efficiency rather than technological boundaries, sample size condition where the total number of DMUs must be 3times higher than total number of inputs. In order to eliminate some of the disadvantages, we tried to combine the DEA method with the regression analysis and to determine which environmental variables have influenced the healthcare efficiency in Slovakia. The results of the regression analysis have confirmed that the environmental (external) variables „public costs“, „private costs“, „departments“, „education“, „population over 65“, „life expectancy“, „wage costs“, „population size“ and „income inequality indicator s80/s20“ are statistically significant and therefore affect the efficiency of healthcare facilities.

References

BANKER, R. D. – CHARNES, A. – COOPER, W. W. (1984): Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. Management Science, *30*, No. 9, pp. 1078 – 1092.

BARAY, J. – CLIQUET, G. (2013): Optimizing Locations through a Maximum Covering/p-median Hierarchical Model: Maternity hospitals in France. Journal of Business Research, *66*, No. 1, pp. 127 – 132.

BELCIUG, S. – GORUNESCU, F. (2015): Improving Hospital Bed Occupancy and Resource Utilization through Queuing Modelling and Evolutionary Computation. Journal of Biomedical Informatics, *53*, February, pp. 261 – 269.

CHANG, L. – LAN, Y. W. (2010): Has the National Health Insurance Scheme Improved Hospital Efficiency in Taiwan? Identifying Factors that Affects its Efficiency. African Journal of Business Management, *4*, No. 17, pp. 3752 – 3760.

CHARNES, A. – COOPER, W. W. – RHODES, E. (1978): Measuring the Efficiency of Decision Making Units. European Journal of Operational Research, *2*, No. 6, pp. 429 – 444.

CHENG, Z. – CAI, M. – TAO, H. – HE, Z. – LIN, X. – LIN, H. – ZUO, Y. (2016): Efficiency and Productivity Measurement of Rural Township Hospitals in China: A Bootstrapping Data Envelopment Analysis. BMJ Open, *6*, No. 11, pp. 1 – 10.

CHOWDHURY, H. – ZELENYUK, V. (2016): Performance of Hospital Services in Ontario: DEA with Truncated Regression Approach. Omega, *63*, September, pp. 111 – 122.

COOPER, W. W. – SEIFORD, L. M. – TONE, K. (2007): Data Envelopment Analysis. A Comprehensive Text with Models, Applications, References and DEA-Solver Software. New York: Springer. ISBN 0387452818.

CROISSANT, Y. – MILLO, G. (2008): Panel Data Econometrics in R: The Plm Package. Journal of Statistical Software, *27*, No. 2, pp. 1 – 43.

CZYPIONKA, T. – KRAUS, M. – MAYER, S. – RÖHRLING, G. (2014): Efficiency, Ownership, and Financing of Hospitals: The Case of Austria. Health Care Management Science, *17*, No. 4, pp. 331 – 347.

DY, M. S. – KILEY, K. B. – AST, K. – LUPU, D. – NORTON, S. A. – McMILLAN, S. C. – HERR, K. – ROTELLA, J. D. – CASARETT, D. J. (2015): Measuring What Matters: Top-Ranked Quality Indicators for Hospice and Palliative Care from the American Academy of Hospice and Palliative Medicine and Hospice and Palliative Nurses Association. Journal of Pain and Symptom Management, *49*, No. 4, pp. 773 – 781.

FARRELL, M. J. (1957): The Measurement of Productive Efficiency. Journal of the Royal Statistical Society, *120*, No. 3, pp. 253 – 290.

FRAGKIADAKIS, G. – DOUMPOS, M. – ZOPOUNIDIS, C. – GERMAIN, C. (2016): Operational and Economic Efficiency Analysis of Public Hospitals in Greece. Annals of Operations Research, *247*, No. 2, pp. 787 – 806.

GERDTHAM, U. G. – LÖTHGREN, M. – TAMBOUR, M. – REHNBERG, M. (1999): Internal Markets and Health Care Efficiency: A Multiple-Output Stochastic Frontier Analysis. Health Economics, *8*, No. 2, pp. 151 – 164.

GREENE, W. H. (2012): Econometric Analysis. Pearson Education Limited. ISBN 978-0-273-75356-8.

HERNANDEZ, A. R. – SAN SEBASTIAN, M. (2014): Assessing the Technical Efficiency of Health Posts in Rural Guatemala: A Data Envelopment Analysis. Global Health Action, *7*, No. 1. Available at: <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3901389/>.

JABLONSKÝ, J. – DLOUHÝ, M. (2004): Modely hodnocení efektivnosti produkčních jednotek. Praha: Professional Publishing. ISBN 80-86419-49-5.

JIA, T. – YUAN, H. (2017): The Application of DEA (Data Envelopment Analysis) Window Analysis in the Assessment of Influence on Operational Efficiencies after the Establishment of Branched Hospitals. BMC Health Services Research, *17*, No. 1, pp. 265 – 273.

KOOREMAN, P. (1994): Data Envelopment Analysis and Parametric Frontier Estimation: Complementary Tools. Journal of Health Economics, *13*, No. 3, pp. 345 – 346.

LACKO, R. – BOSAKOVA, L. – KUBAK, M. – NEMEC, J. – TKAC, M. (2014): Technical Efficiency of Selected Private Hospitals in Slovakia. In: Proceedings of the 18th International Conference on Current Trends in Public Sector Research. [Proceeding.] Brno: Masaryk University, pp. 269 – 275.

LI, H. – DONG, S. (2015): Measuring and Benchmarking Technical Efficiency of Public Hospitals in Tianjin, China A Bootstrap – Data Envelopment Analysis Approach. INQUIRY: The Journal of Health Care Organization, Provision, and Financing, *52*, September, pp. 1 – 5.

MAESTRE, A. M. – OLIVEIRA, M. D. – BARBOSA-PÓVOA, A. P. (2015): Location-Allocation Approaches for Hospital Network Planning under Uncertainty. European Journal of Operational Research, *240*, No. 3, pp. 791 – 806.

MAHATE, A. – HAMIDI, S. – AKINCI, F. (2016): Measuring the Effect of Size on Technical Efficiency of the United Arab Emirates Hospitals. Global Journal of Health Science, *9*, No. 3, pp. 116 – 127.

MANIADAKIS, N. – THANASSOULIS, E. (2000): Assessing Productivity Changes in UK Hospitals Reflecting Technology and Input Prices. Applied Economics, *32*, No. 12, pp. 1575 – 1589.

MITROPOULOS, P. – KOUNETAS, K. – MITROPOULOS, I. (2016): Factors Affecting Primary Health Care Centres' Economic and Production Efficiency. Annals of Operations Research, *247*, No. 2, pp. 807 – 822.

MITROPOULOS, P. – MITROPOULOS, I. – SISSOURAS, A. (2013): Managing for Efficiency in Health Care: The Case of Greek Public Hospitals. The European Journal of Health Economics, *14*, No. 6, pp. 929 – 938.

MUJASI, P. N. – ASBU, E. Z. – PUIG-JUNOY, J. (2016): How Efficient are Referral Hospitals in Uganda? A Data Envelopment Analysis and Tobit Regression Approach. BMC Health Services Research, *16*, No. 1, pp. 230 – 244.

MURA, L. – ORLIKOVA, M. (2016): Social Entrepreneurship and Social Enterprises: The Case of Slovakia. Social Entrepreneurship and Social Enterprises: The Case of Slovakia. In: Proceedings of the 4th International Conference Innovation Management, Entrepreneurship and Corporate Sustainability. [Proceeding.] Prague: University of Economics, pp. 495 – 505.

OIKONOMOU, N. – TOUNTAS, Y. – MARIOLIS, A. – SOULIOTIS, K. – ATHANASAKIS, K. – KYRIOPOULOS, J. (2016): Measuring the Efficiency of the Greek Rural Primary Health Care Using a Restricted DEA Model: The Case of Southern and Western Greece. Health Care Management Science, *19*, No. 4, pp. 313 – 325.

PERERA, R. – DOWELL, A. – CRAMPTON, P. (2012): Painting by Numbers: A Guide for Systematically Developing Indicators of Performance at any Level of Health Care. Health Policy, *108*, No. 1, pp. 49 – 59.

RAMIREZ-VALDIVIA, M. T. – MATURANA, S. – SALVO-GARRIDO, S. (2011): A Multiple Stage Approach for Performance Improvement of Primary Healthcare Practice. Journal of Medical Systems, *35*, No. 5, pp. 1015 – 1028.

RETZLAFF-ROBERTS, D. – CHANG, C. F. – RUBIN, R. M. (2004): Technical Efficiency in the Use of Health Care Resources: A Comparison of OECD Countries. Health Policy, *69*, No. 1, pp. 55 – 72.

SAMUT, P. K. – CAFRI, R. (2015): Analysis of the Efficiency Determinants of Health Systems in OECD Countries by DEA and Panel Tobit. Social Indicators Research, *129*, No. 1, pp. 113 – 132.

SEN, A. – SRIVASTAVA, M. (2012): Regression Analysis: Theory, Methods, and Applications. New York: Springer. ISBN 978-1-4612-4470-7.

SENDEK, S. – SVITÁLKOVÁ, Z. – ANGELOVIČOVÁ, K. (2015): Efficiency Evaluation of Hospitals in the Environment of the Czech and Slovak Republic. Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis, *63*, No. 6, pp. 2109 – 2118.

VARABYOVA, Y. – SCHREYÖGG, J. (2013): International Comparisons of the Technical Efficiency of the Hospital Sector: Panel Data Analysis of OECD Countries Using Parametric and Non-parametric Approaches. Health Policy, *112*, No. 1 – 2, pp. 70 – 79.

WOOLDRIDGE, J. M. (2015): Introductory Econometrics: A Modern Approach. Toronto, ON: Nelson Education. ISBN 9781305446380.