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An Application of DEA Methodology in Efficiency Measurement of the Czech Public Universities

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Abstract

The largest amount of budget of the Ministry of Education, Youth and Sport intended for Czech higher education institutions (HEIs) goes to the public universities and therefore we focused on the measuring their efficiency. We used data envelopment analysis, a non-parametric method, which evaluates the technical efficiency of homogenous production units. We used data for the Czech public HEIs from 2013 and determined the following variables: the academic staff and other costs as inputs and the bachelor and master's graduates and students, PhD graduates and students as outputs. We run two analyses. The first analysis compared all HEIs with each other and showed that we have to consider the specification of the HEIs. The second analysis divided HEIs into three groups with similar cost coefficients and showed that dividing HEIs into groups helped us to eliminate the high differences in inputs and in outputs and therefore we got better information about the efficiency of HEIs. For other analysis we recommend using faculties or departments with the same or similar specialization instead of the whole HEIs.

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Keywords: Efficiency; Data envelopment analysis; Higher education institutions; Public universities

1. Introduction

The Czech higher education system includes three types of the higher education institutions (hereafter HEIs) – 26 public universities, 43 private universities and 2 state universities. Public and private HEIs are financially supported by the Ministry of Education, Youth and Sport (hereafter MEYS). MEYS is the second largest chapter in the state

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budget. Expenses of MEYS were 138 443 mil. CZK in 2013, which represents 11.8 % of the state budget (Monitor, 2014). The planned amount of expenses of MEYS is 137 301 mil. CZK for 2014. 21 771 mil. CZK (15.9 % of MEYS's budget) is intended for the HEIs and 16 526 mil. CZK (12.0 % of MEYS's budget) is intended for research, experimental development and innovation (Act no. 475/2013 Coll.)

MEYS has own calculation about how to distribute money among the HEIs, but there is no mechanism to ascertain whether the money is handled efficiently or not. Therefore we introduce one method – Data Envelopment Analysis, which can be used for measuring the efficiency. In view of the fact that the largest amount of budget (99.7 %) intended for HEIs goes to the public universities (MEYS, 2014a), we focused on the measuring the efficiency of the public universities (see Table 4 in appendix).

Generally if we want to measure the efficiency of a production unit, we will compare inputs and outputs. There are a lot of methods, which can be used, e.g. parametric and non-parametric methods. Parametric methods, e.g. Stochastic Frontier Analysis (SFA), are stochastic and set the concrete production function, usually cost or profit function. Non-parametric methods, e.g. Data Envelopment Analysis (DEA) or Free Disposal Hull (FDH), are deterministic and, in general, determine a ratio of weighted sum of inputs and weighted sum of outputs (Polouček et al., 2006).

A very popular method to measure the efficiency is DEA. Tavares (2002) states, that there were over 3 000 articles and works from over 2 000 authors about DEA published between 1978 and 2001. Today, the number of articles is higher, for example the server DEAzone.com regularly updates its bibliography, which contains over 4 000 articles about using DEA.

DEA in its present form was first introduced in 1978 by Charnes, Cooper and Rhodes. It is based on Farrell's seminal article 'The Measurement of Productive Efficiency' from 1957. Farrell (1957) introduced a model, which measured the efficiency of production units with one input and one output. It was the inception of DEA. Then Charnes, Cooper and Rhodes (1978) proposed a CCR model (according to their names it is called CCR model) which assumed constant returns to scale (CRS). Then Banker, Charnes and Cooper (1984) introduced a BCC model which assumed variable returns to scale (VRS).

It is possible to use DEA for measuring the efficiency of banks, department stores and supermarkets, and extend to car makers, hospitals, schools, public universities, public libraries and so forth. It is not necessary to express inputs and outputs in monetary form. We can also use non-monetary factors (Cooper et al., 2007).

This paper is set up as follows. Section 2 introduces DEA and its basic models – CCR model and BCC model. The focus is on the input-oriented model, which will be used in our analysis. It also demonstrates the strengths and limitations of DEA. The literature review of using DEA for measuring the efficiency of HEIs is presented in Section 3. Section 4 describes the data and model specification. The results of measuring the efficiency of the Czech public universities by using DEA are discussed in Section 5.

2. Data Envelopment Analysis Methodology

DEA is a non-parametric method which is used to evaluate the technical efficiency of homogenous production units. Technical efficiency is defined as the ratio of the weighted sum of outputs to the weighted sum of inputs (Flegg et al., 2003). A homogenous production unit is referred to as a decision making unit (DMU).

Charnes, Cooper and Rhodes (1978) used the name decision making unit to describe the units being analyzed in DEA. This term emphasizes the fact that the focus is not on profit. DMUs are units which produce identical or equivalent outputs and may include banks, supermarkets, hospitals, schools, public universities, public libraries and so forth (Cooper et al., 2007).

DEA is the optimization method of mathematical programming. Its aim is to divide production units into efficient and inefficient production units. DEA can measure the efficiency of DMU with multiple inputs and multiple outputs. The inputs and outputs can be expressed in monetary and non-monetary form (e.g. in the area of education: the number of academic staff, the number of non-academic staff or financial resources as inputs and the number of students, the number of graduates or research quantum as outputs; Cunha and Rocha, 2012).

Using DEA we also are able to design a virtual (hypothetical) unit for each inefficient unit. Virtual units are a part of the efficient frontier and are calculated as a combination of selected efficient units. These selected units are called peer units or peers. Sometimes the efficient unit can be the virtual unit for the inefficient unit.

There are two basic DEA models – CCR model assuming the constant returns to scale and BCC model assuming the variable returns to scale. Both models can be input- and output-oriented.

2.1. Input-oriented CCR model and BCC model

The first DEA model was introduced by Charnes, Cooper and Rhodes (1978). This model maximizes the efficiency rate of a unit, which is expressed as a ratio of weighted outputs and weighted inputs (1), considering constant returns to scale. Formally, the efficiency of DMU can be calculated by solving the following linear fractional programming problem:

$$\text{maximize} \qquad z = \frac{\sum_{i}^{r} u_i y_{iq}}{\sum_{j}^{m} v_j x_{jq}} \tag{1}$$

$$\text{subject to} \qquad \sum_{i}^{r} u_i y_{ik} \le \sum_{j}^{m} v_j x_{jk}, k = 1, 2, \ldots, n \tag{2}$$

$$u_i \ge \varepsilon, i = 1, 2, \ldots, r \tag{3}$$

$$v_j \ge \varepsilon, j = 1, 2, \ldots, m \tag{4}$$

where
z = value of efficiency of DMUq,
ε = infinitesimal constant,
x_{jk} = value of j-th input for DMU_k,
y_{ik} = value of i-th output for DMU_k,
v_j = weight of input,
u_i = weight of output.

Infinitesimal constant ε ensures all weights of inputs and outputs to be positive. The numerator is maximized and the denominator is minimized, which means there is infinite number of solutions. Therefore we transform this formulation into linear programming. Now we can determine a constant:

$$\sum_{j}^{m} v_j x_{jq} = 1 \tag{5}$$

This formula means that the sum of all inputs is equal to 1. The final formula of linear programming for DMU, which is equivalent to linear fractional programming, can be written in the following form:

$$\text{maximize} \qquad z = \sum_{i}^{r} u_i y_{iq} \tag{6}$$

subject to conditions (2), (3), (4) and (5).

DMU will be CCR-efficient, if the optimal value of efficiency is equal to 1. Inefficient units have value of efficiency less than 1. The model (6) is called input-oriented CCR primal model.

BCC model was introduced by Banker, Charnes and Cooper (1984). This model is a modification of CCR model. It assumes variable returns to scale. For allowing VRS, it is necessary to add the convexity condition into the CCR model. This condition ensures that inefficient DMU will be compared with DMU, which has a similar size. Then the input-oriented BCC primal model for DMU is defined in following form:

$$\text{maximize} \qquad z = \sum_{i}^{r} u_i y_{iq} + \mu \tag{7}$$

$$\text{subject to conditions} \ \sum_{i}^{r} u_i y_{ik} + \mu \leq \sum_{j}^{m} v_j x_{jk}, \ (3), (4), (5) \text{ and } \mu \in R,$$

where μ = dual variable matched with the convexity condition.

There is the fact, which is characteristic for all linear programming models. The large amount of conditions and restrictions has the negative impact on the solution of the problem. It is more practical to construct the dual models of linear programming for primal. This dual model uses the same data but with less restrictions (for the calculation procedure using the dual model see Jablonský and Dlouhý, 2004).

As we can see there is only one difference in formula between the CCR model and BCC model. It is the variable μ. The variables μ is equal to 0 for CCR model, but for BCC model they can be positive, negative value or equal to 0 (Jablonský and Dlouhý, 2004). If DMU is efficient according to the CCR model, it will be efficient according to the BCC model too, but not vice versa (Stavárek, 2004).

The output-oriented model works on the same principle as the input-oriented model. The only difference is determined condition. The sum of all outputs is equal to 1.

2.2. Strengths and Limitations of DEA

DEA can be a powerful tool when used wisely. Cornuejols and Trick (1998) states a few of the characteristics that make DEA powerful, for example, DEA can handle multiple input and multiple output models. It doesn't require an assumption of a functional form relating inputs to outputs and DMUs are directly compared against a peer or combination of peers.

Cornuejols and Trick (1998) also warns that the same characteristics that make DEA a powerful tool can also create problems; for example, since DEA is an extreme point technique, noise (even symmetrical noise with zero mean) such as measurement error can cause significant problems. DEA measures 'relative' efficiency, not 'absolute' efficiency. In other words, it can tell you how well you are doing compared to your peers but not compared to a 'theoretical maximum'. Since DEA is a nonparametric technique, statistical hypothesis tests are difficult. Since a standard formulation of DEA creates a separate linear program for each DMU, large problems can be computationally intensive.

3. Literature review

In recent years, several studies have undertaken analysis of efficiency of public universities using DEA methodology.

McMillan and Datta (1998) used DEA to measure the efficiency of 45 Canadian universities using 1992-1993 data. They constructed nine models, which differ in inputs (the number of faculties, other costs, total costs, etc.) and in outputs (the number of graduates, the number of doctoral level graduate students, research quantum, etc.). Their results showed that the average university is about 0.94 efficient. Despite the limitations of DEA they believe that this method is useful. They also recommended measuring the efficiency of the units, which are more homogenous, e.g. faculties or departments.

Avkiran (2001) measured the efficiency of 36 public universities in Australia. He constructed three models based on 1995 data: Overall performance (model 1), Performance on delivery of educational services (model 2) and Performance on fee-paying enrolments (model 3). All these models had the number of academic staff and the number of non-academic staff as the inputs. The outputs were different in each model (model 1: undergraduate enrolments, postgraduate enrolments, research quantum; model 2: student retention rate, student progress rate, graduate full-time employment rate; model 3: overseas fee-paying enrolments, non-overseas fee-paying postgraduate enrolments). He found out that the average efficiency score of universities is 0.9553 for model 1, 0.9667 for model 2 and 0.6339 for model 3. Model 3 confirmed the poor performance on attracting fee-paying students.

Abbott and Doucouliagos (2003) used the same data as Avkiran (2001), i.e. 36 Australian universities in 1995. They focused on the outputs of research and teaching. They constructed a few models and used the number of equivalent full-time students, the number of postgraduate and undergraduate degrees enrolled, the number of postgraduate degrees conferred and the number of undergraduate degrees conferred as outputs for measuring the teaching output. The research output is measured by the research quantum allocation that each university received. The four inputs were used: the number of academic staff, the number of non-academic staff, expenditure on all other inputs other than labour inputs and the value of non-current assets. Their results showed that Australian universities evince the high level of efficiency relative to each other (the average efficiency score from all models is in the interval 0.946 – 0.967). They also found out that using three or four outputs does not alter the results.

Afonso and Santos (2005) measured the efficiency of 52 Portuguese universities, faculties and institutes. The data set contained 2003 data. They constructed five models which had one input and one output, two inputs and one output or two inputs and two outputs. They used the average total spending per student and the teachers-to-students ratio as inputs. The outputs were represented by the success rate of undergraduate students and the number of doctoral dissertations. Their results showed that the overall input efficiency is between 0.553 and 0.678, therefore it seems to be some theoretical 'waste' of resources. On the other hand, the overall output efficiency scores are between 0.728 and 0.828.

Kempkes and Pohl (2007) analysed the efficiency of 72 public German universities for the years 1998 – 2003. They used the number of graduates and the amount of research grants as outputs and the technical staff, the research staff and current expenditure as inputs. They also compared the East German universities to the West German counterparts. They concluded that the East German universities are less efficient than the West German counterparts and the size of the university is not necessarily associated with its efficiency.

Cuenca (2011) measured the performance of 78 state universities and colleges in the Philippines in the period 2006-2009. She used available data for DEA analysis, for example, expenditure data as inputs and the number of enrolled students, the number of graduates and total revenue as outputs. Her results showed that the majority of the state universities and colleges have efficiency score less than 1. The average efficiency score was 0.850 in 2006, 0.845 in 2007, 0.742 in 2008 and 0.772 in 2009.

Cunha and Rocha (2012) analysed the public universities in Portugal, which were differed in three groups: 14 public universities, 20 polytechnics and 14 faculties of the University of Porto. All data refer to the year 2008. They used total funding per student, total expenditure per student and the academic staff per student as inputs and total graduate students, total PhD degrees awarded and total number of courses as outputs. They concluded that a large portion of institutions may be working inefficiently and it contributes to a significant waste of resources. The average efficiency score is 0.8321 for the public universities, 0.7793 for the public polytechnics and 0.8250 for the faculties of the University of Porto.

4. Data and model specification

We used data for the Czech public HEIs from 2013 and input-oriented BCC models. According to the foreign authors we chose the following variables: the number of academic staff and other costs as inputs and the number of bachelor and master's graduates, the number of PhD graduates, the number of bachelor and master's students and the number PhD students as outputs.

The academic staff (see Avkiran, 2001; Abbott and Doucouliagos, 2003) contains professors, associate professors, assistant professors, lecturers, assistants and teaching staff. The other costs (see McMillan and Datta, 1998; Abbott and Doucouliagos, 2003) contains material consumption, energy consumption, repair and maintenance, other services, other expenditure and depreciation of tangible and intangible assets. There are no wages costs included and we did not use them as other input, because they are strongly positively correlated with the number of academic staff (the correlation coefficient is 93.83 %). Using the number of academic staff and the wages costs as inputs separated in two models showed very similar results.

The number of bachelor and master's students (see Abbott and Doucouligos, 2003) was calculated as the sum of all internal and external students in a bachelor and master's program. There, in the Czech Republic, are three modes of studying. The internal students study in the full-time mode and the external students study in the distance mode and in the combined mode, therefore we calculated the external students with half the weight. The number of PhD students was also calculated as the sum of all internal and (with half the weight) external students in a doctoral program. The same calculation was used for the number of bachelor and master's graduates (see McMillan and Datta, 1998; Abbott and Doucouligos, 2003; Kempkes and Pohl, 2007; Cuenca, 2011) and the number of PhD graduates (see Abbott and Doucouliagos, 2003; Afonso and Santos, 2005).

Using these variables we constructed eight models. All of them are input-oriented and with variable returns to scale. The choice of input- or output-oriented model is bases on the control of the administrator of the university (Kempkes and Pohl, 2007). We believe that they can control the number of academic staff and costs better than the number of students and the number of graduates.

Abbott and Doucouliagos (2003) found out that it is possible that the choice of inputs and outputs can influence how the efficiency scores are ranked. Therefore we constructed eight models with one input and one output to see how the selected input and the selected output can influence the efficiency scores (see Table 1).

Table 1. Eight models and their inputs and outputs.

Model	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Input	Other Costs	Other Costs	Acad. Staff	Acad. Staff	Other Costs	Other Costs	Acad. Staff	Acad. Staff
Output	Grad. 1	Stud. 1	Grad. 1	Stud. 1	Grad. 2	Stud. 2	Grad. 2	Stud. 2

Source: Author.

Note: Grad. 1 = Bachelor and master's graduates, Grad. 2 = PhD graduates, Stud. 1 = Bachelor and master's students, Stud. 2 = PhD students.

Descriptive statistics (minimum, maximum, mean, median and standard deviation) of the data sets is presented in Table 2. Data for the analysis were used from the Ministry of Education, Youth and Sport (MEYS, 2014b). The calculation was performed by using DEA-Excel Solver 2014 (Jablonský, 2014).

Table 2. Descriptive statistics of data set of the Czech public universities (in 2013).

Variable	**Min.**	**Max.**	**Mean**	**Median**	**Std. Dev.**
Academic staff	58.5	3 520.3	577.9	409.2	661.2
Other costs (in thousands CZK)	47 294.8	3 842 054.9	885 823.8	567 361.5	941 384.2
Bachelor and master's graduates	64.0	7 862.5	2 562.2	2 011.3	2 166.8
PhD graduates	0.0	373.0	57.3	35.0	77.6
Bachelor and master's students	299.0	38 691.5	10 659.2	8 562.8	9 304.1
PhD students	0.0	5 418.5	725.4	355.5	1 117.5

Source: Calculated by author based on the data from MEYS (2014b)

5. Results and discussion

We ran the analysis, where we used 26 public HEIs in eight different models. The results showed the large differences between the HEIs in one model and also between the models themself. As an example we mention the HEIs UVPS and ICT. Their efficiency scores are the lowest in Model 1, Model 2, Model 3 and Model 4 (UVPS – 0.127, 0.098, 0.340 and 0.275 and ICT – 0.136, 0.108, 0.260 and 0.211). This inefficiency is given by the high costs per graduate and per student in Model 1 and Model 2. Their other costs per graduate are three times higher than the average and other costs per student are twice as high as the average. These HEIs are inefficient according to the DEA in Model 3 and Model 4 because their ratios graduates/teacher and students/teacher represent only half the average. This is caused by the specialization of these HEIs (UVPS – veterinary medicine and pharmaceutical sciences and ICT – chemical technology). This is also typical for art HEIs (e.g. APA). The same problem occurs in Model 5, Model 6, Model 7 and Model 8.

The results indicate that the efficiency score is sensitive to the selected inputs and selected outputs. Using more variables in model decreases the sensitivity and thus increases the efficiency scores. McMillan and Datta (1998) recommend keeping the number of variables less than one-third of the number of observations. It is also important to consider factors like the specialization of the HEI. The specialization of UVPS requires high costs and therefore its efficiency score is influenced by the inputs. Its other costs are high and the ratios graduates/teacher and students/teacher are low. It is because veterinary medicine and pharmaceutical sciences require high costs and there are more teachers per graduates and students than in other HEIs with, for example, specialization in economics (e.g. UE).

According to this conclusion we divided HEIs into groups with the similar specialization. There are HEIs, which do not have only one specialization (e.g. CU), and therefore we used cost coefficients. MEYS divides study programs into seven groups according to the relative costs. The relative costs are represented by cost coefficients, which are between 1.00 (for economics, humanities) and 5.90 (for art). We calculated total cost coefficient for each HEI as a weighted average. We used the equivalent number of students in study programs as a weight.

According to the total cost coefficients we divided HEIs into three groups with similar coefficients. The average of total cost coefficients of Group 1 is 1.28, of Group 2 1.60 and of Group 3 5.82. UE (with the total cost coefficient 1.08), ICT (2.72) and UVPS (3.15) are not included, because they are outliers of these groups. UE is economic HEI, the specialization of ICT is chemical technology and the specialization of UVPS is veterinary medicine and pharmaceutical sciences and there are no other HEIs with the same or similar specialization.

We used the same data and models as in the first analysis. The results of the second analysis are presented in Table 3 in appendix. It is obvious that the efficiency scores are higher than in the first analysis. Using the total cost coefficients and dividing HEIs into groups we eliminated the high differences in inputs and in outputs.

Although we divided the HEIs into the groups, which are more homogenous, we can still find HEIs with low efficiency score (Group 1: Model 7 – UHK and SU, Model 8 – UHK, SU and UWB; Group 2: Model 1 and Model 2 – UP, Model 5 – BUT, Model 6 – MUB; Group 3: Model 7 – JAMPA). Group 1 and Group 3 are small (six and four HEIs) and we used model with variable returns to scale; therefore there is a lot of efficient HEIs in each model. Group 2 has thirteen HEIs. The significant differences between the results of the first and second analysis are as follows; in the first analysis, CU was efficient in six models and inefficient in Model 1 (0.704) and Model 3 (0.296). In the second analysis, CU is efficient in all models. In the first analysis, OU is inefficient in all models. In the second analysis, OU is efficient in four models (all models with other costs as input). Its efficiency score in other four models is also higher than in the first analysis. In the first analysis, CULS was efficient only in one model. In the second analysis, CULS was efficient in five models. Using groups led to better comparability of HEIs.

For other analysis, we recommend using faculties or departments as DMUs with the same or similar specialization. DMUs can be divided into groups as follows: economics, philosophy, engineering, agriculture, medicine, art, etc. (for comparison see McMillan and Datta, 1998).

6. Conclusion

The Czech universities are financially supported by MEYS. 99.7 % of budget, which is intended for public and private HEIs, goes to the public HEIs. Therefore we measured the efficiency of the public HEIs. For measuring the efficiency we used the DEA methodology. DEA is the optimization method of mathematical programming. Its aim is to divide production units into efficient and inefficient production units by comparing each production unit with its peer units. We chose the following variables: the number of academic staff and other costs as inputs and the number of bachelor and master's graduates, the number of PhD graduates, the number of bachelor and master's students and the number PhD students as outputs. We constructed eight models using data from 2013 and input-oriented BCC model.

We run two analyses. The first analysis compared all HEIs with each other. The second one divided HEIs into three groups with similar cost coefficients. The first analysis showed that we have to consider the specification of the HEIs. We mentioned UVPS as an example. The specialization of UVPS (veterinary medicine and pharmaceutical sciences) requires high costs and therefore its efficiency score was low in the first analysis. In the second analysis, dividing HEIs into three groups helped us to eliminate the high differences in inputs and in outputs. The results showed higher efficiency scores than in the first analysis. The creation of groups of HEIs with similar specialization gave us better information about their efficiency; therefore we recommend going deeper and using faculties or departments as DMUs with the same or similar specialization. DMUs can be divided into following groups: economics, philosophy, engineering, agriculture, medicine, art, etc.

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Appendix

Table 3. The efficiency scores of the Czech public universities divided into three groups based on cost coefficients (in 2013).

HEIs	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
Input	Other Costs	Other Costs	Acad. Staff	Acad. Staff	Other Costs	Other Costs	Acad. Staff	Acad. Staff
Output	Grad. 1	Stud. 1	Grad. 1	Stud. 1	Grad. 2	Stud. 2	Grad. 2	Stud. 2
GROUP 1								
MU	1	1	1	1	1	1	1	1
UHK	0.904	1	0.778	0.675	0.567	0.659	0.360	0.369
SU	1	1	0.861	0.632	1	1	0.492	0.457
UWB	0.829	0.797	0.690	0.620	0.731	0.695	0.509	0.477
CPJ	1	0.781	1	0.820	0.781	0.781	0.820	0.820
ITB	1	1	1	1	1	1	1	1
Mean	*0.955*	*0.930*	*0.888*	*0.791*	*0.846*	*0.856*	*0.697*	*0.687*
Std. dev.	*0.067*	*0.100*	*0.122*	*0.161*	*0.167*	*0.149*	*0.255*	*0.262*
GROUP 2								
CU	1	1	1	1	1	1	1	1
USB	0.823	0.803	0.637	0.704	1	0.856	0.711	0.735
JEPU	0.893	0.893	0.933	0.933	0.893	0.893	0.933	0.933
PU	0.563	0.589	0.759	0.788	0.603	0.575	0.966	0.961
OU	1	1	0.883	0.887	1	1	0.883	0.883
CTU	0.606	0.506	0.527	0.524	0.526	0.553	0.663	0.700
TUL	0.583	0.583	0.941	0.941	0.583	0.626	0.941	0.948
UP	0.425	0.466	0.958	0.989	0.537	0.521	0.985	1
BUT	0.882	0.593	1	0.946	0.415	0.557	0.685	1
TUO	0.754	0.639	0.695	0.642	0.603	0.587	0.621	0.719
TBU	0.812	0.556	1	1	0.627	0.580	1	1
CULS	1	1	1	1	0.871	0.551	1	0.812
MUB	0.508	0.436	0.863	0.920	0.743	0.486	1	0.957
Mean	*0.758*	*0.697*	*0.861*	*0.867*	*0.723*	*0.676*	*0.876*	*0.896*
Std. dev.	*0.192*	*0.204*	*0.151*	*0.149*	*0.197*	*0.181*	*0.142*	*0.110*
GROUP 3								
APA	1	1	1	1	1	1	1	1
AFA	1	1	1	1	1	1	1	1
AAAD	0.727	0.777	1	1	0.954	0.623	1	0.806
JAMPA	1	1	0.892	0.690	1	1	0.488	0.760
Mean	*0.932*	*0.944*	*0.973*	*0.922*	*0.988*	*0.906*	*0.872*	*0.892*
Std. dev.	*0.118*	*0.096*	*0.047*	*0.134*	*0.020*	*0.163*	*0.222*	*0.110*

Source: Calculated by author based on the data from MEYS (2014b)

Note: Grad. 1 = Bachelor and master's graduates, Grad. 2 = PhD graduates, Stud. 1 = Bachelor and master's students, Stud. 2 = PhD students.

Table 4. Definitions of abbreviations of the Czech HEIs.

Abbreviation	Name of the Czech public university
CU	Charles University in Prague
USB	University of South Bohemia in České Budějovice
JEPU	Jan Evangelista Purkyně University in Ústí nad Labem
MU	Masaryk University
PU	Palacký University of Olomouc
UVPS	University of Veterinary and Pharmaceutical Sciences, Brno
OU	University of Ostrava
UHK	University of Hradec Králové
SU	Silesian University, Opava
CTU	Czech Technical University in Prague
ICT	Institute of Chemical Technology in Prague
UWB	University of West Bohemia
TUL	Technical University of Liberec
UP	University of Pardubice
BUT	Brno University of Technology
TUO	Technical University of Ostrava
TBU	Tomas Bata University in Zlín
UE	University of Economics, Prague
CULS	Czech University of Life Sciences Prague
MUB	Mendel Univesity Brno
APA	Academy of Performing Arts in Prague
AFA	Academy of Fine Arts, Prague
AAAD	Academy of Arts, Architecture and Design in Prague
JAMPA	Janáček Academy of Music and Performing Arts
CPJ	College of Polytechnics Jihlava
ITB	The Institute of Technology and Business

References

Abbott, M., Doucouliagos, C., 2003. The efficiency of Australian universities: A data envelopment analysis. Economics of Education Review 22, pp 89-97.

Act no. 475/2013 Coll., On the state budget of the Czech Republic for the year 2014.

Afonso, A., Santos, M., 2005. Students and Teachers: A DEA Approach to the Relative Efficiency of Portuguese Public Universities. NEP: New Economics Papers Education.

Avkiran, N. K., 2001. Investigating technical and scale efficiencies of Australian universities through data envelopment analysis. Socio-Economic Planning Sciences 35, pp 57-80.

Banker, R.D., Charnes, A., Cooper, W.W., 1984. Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. Management Science 30, pp 1078-92.

Charnes, A., Cooper, W.W., Rhodes, E.L., 1978. Measuring the Efficiency of Decision Making Units. European Journal of Operational Research, no. 2 (6), pp 449 - 444.

Cooper, W.W., Seidford, L.M., Tone, K., 2007. Data Envelopment Analysis – A Comprehensive Text with Models, Applications, References and DEA-Solver Software. Springer, 490p, ISBN 978-0-387-45283-8.

Cornuejols, G., Trick, M., 1998. Quantitative Methods for the Management Sciences. Carnegie Mellon University, Pittsburg.

Cuenca. J.S., 2011. Efficiency of State Universities and Colleges in the Philippines: a Data Envelopment Analysis. Discussion Paper Series No. 2011-14.

Cunha, M., Rocha, V., 2012. On the Efficiency of Public Higher Education Institutions in Portugal: An Exploratory Study. The University of Porto.

DEAzone.com, n.d. Bibliography. [Online], Accessed at 18. 11. 2014. Available from: <http://deazone.com/en/resources/bibliography>

Farrell, M.J., 1957. The Measurement of Productive Efficiency. Journal of the Royal Statistical Society, Series A, 120 (3), pp 253 – 290.

Flegg, A.T., Allen, D.O., Field, K., Thurlow, T.W., 2003. Measuring the Efficiency and Productivity of British Universities: An Application of DEA and the Malmquist Approach. School of Economics, University of the West of England, Bristol.

Jablonský, J., Dlouhý, M., 2004. Modely hodnocení efektivnosti produkčních jednotek. 1. vyd. Praha, Professional Publishing, 184p, ISBN 80-86419-49-5.

Jablonský, J., 2014. DEA-Excel Solver 2014 (a MS Excel based system for DEA models). [Online] Accessed at 23. 12. 2014. Available from: <https://webhosting.vse.cz/jablon/>

Kempkes, G., Pohl, C., 2007. The Efficiency of German Universities – Some Evidence from Non-Parametric and Parametric Methods. CESifo Venice Summer Institute 2007, 18-19 July.

McMillan, M.L., Datta, D., 1998. The Relative Efficiencies of Canadian Universities: A DEA Perspective. Canadian Public Policy, vol. 24, No. 4, pp 485-511.

MEYS, 2014a. Rozpis rozpočtu vysokých škol na rok 2014. [Online] Accessed at 16. 11. 2014. Available from: <http://www.msmt.cz/vzdelavani/vysoke-skolstvi/rozpis-rozpoctu-vysokych-skol-na-rok-2014>

MEYS, 2014b. Vysoké školství. [Online] Accessed at 20. 11. 2014. Available from: <http://www.msmt.cz/vzdelavani/vysoke-skolstvi>

MONITOR, 2014. Přehled státního rozpočtu. [Online], Accessed at 16. 11. 2014. Available from: <http://monitor.statnipokladna.cz/en/2013/statni-rozpocet/>

Polouček, S. at al., 2006. Bankovnictví. 1. Edition. Praha, C. H. Beck, ISBN 80-7179-462-7.

Stavárek, D., 2004. Efektivnost bank v zemích Visegrádské skupiny. Ostrava, VŠB – Technical University of Ostrava, Faculty of Economics. Doctoral thesis.

Tavares, G., 2002. A Bibliography of data Envelopment Analysis (1978-2001). Rutcor Research Report. Piscartaway, New Jersey: Rutgers University.