EFFICIENCY ANALYSIS OF A HUNGARIAN PUBLIC ADMINISTRATIVE INSTITUTION WITH DATA ENVELOPMENT ANALYSIS

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Abstract

Measuring the performance of public administration tasks and increasing efficiency is an important problem in the operation of public sector organizations. This paper illustrates the application of data envelopment analysis (DEA) through an efficiency study of a public administration institution and highlights several theoretical and applied research opportunities. In the present study, the performance of county directorates of the Hungarian State Treasury (HST) performing payroll accounting activities are compared using DEA. DEA ensures the consideration of the peculiarities of organizational operation and allows for complex efficiency analysis. The the objective of this study is to formulate an efficiency-enhancing proposal for the managers of the HST based on DEA results, thus, human resource management can respond better to changes in the amount of payroll accounting tasks. The analysis of the payroll accounting activity of the HST reflects well the advantages of applying DEA in cases where the result of the examined process cannot be interpreted in economic terms, but there is an economic interest in the efficient operation of the process. The input-oriented constant returns to scale radial model used in the study identifies the efficient organizational units, the main possible causes of inefficiency, and several feasible ways to improve the operation. Furthermore, examining the changes in efficiency over time highlights the dynamic problems of resource planning and task allocation. Our results can shed light on the reasons for inefficient operations, help to rethink the aspects of task allocation and/or headcount management and provide information for decisions related to the organizational and technological development of payroll accounting of the HST.

Points for Practitioners

Internal performance evaluations often rely on standards that assume a consistent operating environment. Thanks to the COVID-19 epidemic, the operating environment has changed in almost every part of the world, just as it has in public administration. In this environment of volatile and new measures, it will be difficult to assess the goodness of operation against standards. Performance analysis using the DEA methodology ranks the organizational units relative to each other based on the weighted ratio of the output they produce to the inputs used for it. A number of models can be set up when applying the methodology, which can take into account external factors or standards, as long as they can be quantified. This paper shows how this objective, mathematically based methodology can be applied for the efficiency analysis of Hungarian county directorates performing public administrative tasks.

Keywords

Data Envelopment Analysis, Efficiency Analysis, Linear Programming, Performance Assessment

1. Introduction

The business and the public sector differ in several basic decision criteria. (Rantanen et al. 2007) The actors of the two sectors have different goals and responsibilities, they differ in the freedom of strategy making, its process and decision-making mechanisms, as well as in the composition and motivations of their customers/clients. (Nemeslaki, 2014) In addition, the interpretation of the concept of efficiency also differs in the

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two sectors. (Mihaiu et al. 2010; Van Dooren et al. 2015) At the same time, increasing efficiency while reducing costs is a key decision criterion not only in the private but also in the public sector.

An important task in public administration is to measure and evaluate efficiency (Orbán, 2016), to compare the operation of organizational units (Bozsó et al. 2016) and to formulate proposals aimed at improving the operations. The literature on the measurement of public sector efficiency uses a variety of techniques and focuses on different units of analysis. (Rogge et al. 2017; Narbón-Perpina & De Witte, 2018) However, there is usually no single indicator that includes all the important elements of the results of the organizational units, and the data used are multidimensional. (Ricci & Civitillo, 2018) Furthermore, organizational output in the public sector and the resources used for generating the output not always have a financial dimension, or if there is one, its use may mislead efficiency analysis. (Koltai & Uzonyi-Kecskés, 2017) The method of data envelopment analysis (DEA) is suitable for solving the outlined problem.

Several international studies show that DEA is an appropriate method for multi-criteria analysis in terms of public sector efficiency analysis. To highlight some examples, Afonso & Kazemi (2017) analyse the efficiency of public spending in OECD countries, following the international comparison of public sector efficiency of Afonso et al. (2005). Aubyn et al. (2005) examine the efficiency of public spending on tertiary education applying two methods, one of which is DEA. In a study covering a completely different topic, the effectiveness of health care in Iran, focusing on dentistry, is examined by Barouni et al. (2017). Another example is Khushalani & Ozcan (2017), who deal with the quality comparison of hospital care while presenting a new DEA model. Gupta & Bolia (2020) uses DEA to measure the efficiency of Indian high courts from a policy perspective. At the same time, public sector tasks also cover environmental protection; Nazarko & Chodakowska (2020) examines the efficiency of public institutions that financially support environmental efforts in Poland. Besides, the analyses of the Slovenian police (Tomaževič et al. 2016), the Slovak administration (Buleca & Mura, 2014), Greek municipalities (Doumpos & Cohen, 2014) or the study of the accountability of public education in Illinois (Chalos & Cherian, 1995) are other DEA-based studies can serve as an example here.

A common element can be discovered when studying the DEA applications within the public sector. Namely, the fact that efficiency is perceived in the same way: by using as few resources as possible for a given result, or by achieving as many results as possible from a given resource.

In this research, a comparative efficiency analysis at the payroll accounting branches of the county directorates of the Hungarian State Treasury (HST) is performed. The methodological basis of the analysis is DEA which is based on linear programming. The main goal is to formulate an efficiency-enhancing proposal for the leaders of the HST based on DEA results, thanks to which the human resource management of the institution performing tasks at the national level can better respond to changes in the amount of payroll accounting tasks. The presented efficiency analysis is based on the relationship between the actual number of staff employed by the county directorates and the items accounted for. In the research, a data set for a full calendar year was used. After reviewing the elements and mathematical relationships of the DEA models used in the study, the results are presented: first, the results of an aggregate study based on annual data, next, the analysis of the monthly change of efficiencies are discussed.

2. Methodology and model

Performance evaluation of production and service systems is based on the comparison of resources used and results gained. If emphasis is placed on examining the relationship between costs and financial results, traditional financial evaluation techniques can be applied, such as balance sheet evaluation, cost variance analysis, cash flow or breakeven analyses. These methods allow the comparison of several different resources and results by converting them into financial dimensions. If one wants to avoid this transformation and compare resources and results in terms of actual volume or value, DEA may be an appropriate tool.

DEA is based on the work of Farrell (1957), formalized later by Charnes et al. (1978) and further developed by Banker et al. (1984). Since then, several models for capturing the special conditions of real life in every area of the for-profit and non-profit sector are developed. DEA is a performance assessment technique that can serve as a decision support tool for management in many cases. This method is able to compare the efficiency of many homogeneous organizational units with multiple inputs and outputs at the same time, thus, it enables complex performance evaluation. It can serve as a tool for supporting management decision-making in defining performance standards that are both feasible and desirable for the organization.

DEA is based on linear programming. It can calculate the relative efficiencies of multiple organizational units based on pure numerical data. The organizational units that are the subject of the comparison are called decision-making units (DMUs). DMUs are regarded as the entity responsible for converting inputs into outputs. In a managerial point of view, DMUs can be, for example, banks, hospitals, for-profit and non-profit organizations, departments or subdivisions and so forth. DEA aims to compare the performance of DMUs which perform the same or similar activity on the basis of the weighted ratio of the results (outputs) they produce and the resources (inputs) used. Thus efficiency score is calculated as the ratio of the weighted inputs to the weighted outputs. The causes of inefficient operation can be identified and specific, numerical performance improvement proposals can be formulated. When analysing the causes of inefficiency, the value of excess resources used and insufficient results are obtained not in financial terms. The proposed changes are expressed in the actual amounts of the related resources and results. This evaluation technique provides clear information on the possible ways to improve efficiency.

DEA results include, among other things, an efficiency score for each DMU that is between 0 and 1, and generally expressed as a percentage between 0 and 100%. Units that prove to be efficient have an efficiency score of 1, while inefficient units' score is less than 1. In the case of an input-oriented approach, an efficiency score of, for example, 0.85 means that the inputs used need to be reduced to 85% of the original quantity. In the case of an output-oriented approach, the same value means that the output produced with the applied amount of input is not sufficient, an additional 15% increase in output is required for efficient performance.

The method can be used also to select the best performers (also called peers) from the units involved in the analysis. They form the reference set of inefficient units. Acquiring their best practices, poorly performing units can improve the efficiency of their operation.

It is important to emphasize that the DMUs are only relatively efficient or inefficient. Based on the data (inputs and outputs) of a specific set of organizational units, we conclude how efficiently a DMU operates. Examining efficient units in another composition of DMUs may result in inefficient operation. Thus, it is possible to perform better than an operation that has been shown to be efficient as a result of the analysis. In each case, the data of the units involved in the current study are decisive in terms of the outcome.

Table 1. List of notations

Indices:		
j	-	index of DMU, $j = 1, \ldots, J$
i	-	index of input, $i = 1, \ldots, I$
k	-	index of output, $r = 1, \ldots, K$
Parameters:		
Y	-	matrix containing the outputs of all DMUs
Y_0	-	vector containing the outputs of the reference DMU
X	-	matrix containing the inputs of all DMUs
X_0	-	vector containing the inputs of the reference DMU
Variables:		
u	-	vector containing the weights of outputs
v	-	vector containing the weights of inputs
θ	-	relative efficiency with the input-oriented approach
θ^*	-	optimal relative efficiency with the input-oriented approach
λ	-	vector containing the dual variables of the input-oriented CCR model
λ_j	-	dual variable of DMU j in the input-oriented model

In the present study, we used an input-oriented (aiming to maintain the current value of outputs with less input), constant returns to scale (CRS; meaning an increase in inputs causes an equally proportional increase in outputs), radial (prescribing an equal reduction of all inputs) DEA model. The theoretical background of the model is detailed in the following paragraphs. Notations used in this paper are listed in *Table 1*.

Let us assume that J number of DMUs are to be evaluated when K different outputs are observed and I different inputs are used. The input-oriented CRS model compares DMUs based on the weighted output and weighted input quantities, and the measure of efficiency is the ratio of weighted output to weighted input. Using a mathematical programming model, the values of the weights at which the efficiency score of the reference DMU (marked with 0) is the highest possible are determined. Since all DMUs have the same weights in the comparison, the ratio of weighted output to weighted input for all DMUs is less than or equal to 1. Model (1) shows the mathematical expression of these principles, that is:

$$\begin{aligned} &\text{Max} \quad \frac{uY_0}{vX_0} \\ &\text{DMU}: \ \frac{uY}{vX} \leq 1 \\ &\qquad\quad u,v \geq 0 \end{aligned} \tag{1}$$

If Model (1) is rearranged to eliminate the ratio of variables, and the weighted input is fixed (equal to 1) to get a unique solution for the linear programming problem, then the primal version of the input-oriented CRS model is obtained as:

$$\begin{aligned} &\text{Max} \quad uY_0 \\ &\text{DMU}: \ uY - vX \leq 0 \\ &\text{Input}: \qquad vX_0 = 1 \\ &\qquad\qquad\quad u,v \geq 0 \end{aligned} \tag{2}$$

The optimal solution gives the relative efficiency of the examined (reference) DMU 0, as well as the weights of the inputs and outputs. In practice, weights provide little information for efficiency improvement decision-making, so it is more appropriate to solve the dual version of Model (2). If θ scalar variable is the dual variable of the input normalization equation and λ_j is the dual variable assigned to DMU j, then the dual form of the input-oriented CRS model can be written as follows:

$$\begin{aligned} &\text{Min} \qquad\qquad \theta \\ &\text{Output}: \ Y\lambda \qquad\quad \geq Y_0 \\ &\text{Input}: \ -X\lambda + \theta X_0 \geq 0 \\ &\qquad\quad \theta \geq 0; \theta \leq 0; \ \lambda \geq 0 \end{aligned} \tag{3}$$

The optimal solution of (3) includes the relative efficiency (θ^*) of the reference DMU, as well as the optimal value of the dual vector variable λ. Based on the optimal solution, the decision-maker of the inefficient DMU ($\theta^*<1$) obtains the proportion (θ^*) by which all its inputs need to be reduced to become efficient. The optimal solution also shows what proportion of the inputs of efficient DMUs need to be combined for an inefficient DMU to be efficient. DMUs with $\lambda_j > 0$ form the reference set of the reference DMU. By using the best practices of the DMUs in the reference set, inefficient DMUs can become better performing. Model (3) is called the CCR input model, the θ^* value obtained when solving the model is called CCR efficiency, and the designated efficiency frontier is called the CCR efficiency frontier. (Charnes et al. 1978).

Note that besides knowing the extent to which all inputs must be reduced, further independent input reduction possibilities can also be explored. This is performed in the second phase of the analysis. The models for this second phase are not detailed here but can be found for example in Cooper et al. (2007).

In the following, efficiency analyses performed at the payroll accounting activities of the HST using Model (3) are presented in details.

3. Application environment

As can be read at the website of the Hungarian State Treasury, HST "is a central budget agency with a separate operation and financial management, with executive power, forming an independent legal entity with a national scope of competence, standing under the direction of the Minister of Finance concerning both the functional and the regulatory aspects. The Treasury performs its tasks through the Headquarters and the County Directorates." The HST employs nearly 6,000 people.

The centralized payroll calculation activities of the Treasury cover the accounting of nearly nine hundred thousand personal salaries and allowances, health insurance benefits and public charges of employers employed in the public sector. During our study, the 19 county directorates of the HST dealing with payroll accounting formed the DMUs (J=19). Based on the understanding of the payroll accounting process a single input was selected jointly with HST management (I =1). The *actual number of payroll accountants* working in the county directorates was chosen as input. Based on the analysis of the items accounted for, two output factors (K=2) were determined: *the weighted sum of accounted items* and *the weighted sum of complicating factors*:

- *The weighted sum of accounted items*: accounted items were divided into three groups according to the current practice at HST, then weighted and cumulated according to standardised ratios applied at the organization. The accounting matters and their weights in parentheses are listed below:
  - status matters (1);
  - public employment matters (1.5);
  - assignment matters (0.5).

- *The weighted sum of complicating factors*: other characteristics of the items that make accounting work more difficult have arisen in determining the outputs. The different effects of these complicating factors were taken into account using the weights recommended by HST experts. The factors complicating the accounting activity and the corresponding weights in parentheses are listed below:
  - number of inter-monthly payments (0.5);
  - number of new public employments (1);
  - number of terminated public employments (1.5);
  - number of discount processes (1.3);
  - number of compensations (1.2);
  - sickness benefits, number of health insurance accounts (1.5);
  - number of accidents at work (2);
  - number of financial deductions (0.3);
  - number of payment disables (1.5);
  - number of pension claims (2);
  - number of external audits (2).

The values of inputs and outputs per month and per county directorate were provided by the HST staff. The study period covers a full year in which no significant organizational and work allocation changes have taken place, thus, the results characterize an established operation.

4. Analyses, results

4.1 Analysis based on annual aggregated data

The main goal of the presented research is to formulate a substantiated proposal for the labour management specialists of the payroll accounting department of the HST. First, the importance of complicating factors was analysed. At this stage the following questions must have been answered: Do the complicating factors play an important role in determining relative efficiency? And if yes, is it important to weight them?

Therefore, the effect of the complicating factors on the results when determining relative efficiencies was analysed. Two different values of the efficiency scores were calculated: first, the complicating factors were not part of the DEA model (1-output model), then the complicating factors were also considered (2-output model).

Grey bars on Figure 1 show the relative efficiencies calculated without the complicating factors, and black bars show the results with the inclusion of them. Based on the results, county directorates that handle more difficult cases prove to be slightly more efficient. This efficiency increase can be observed at DMUs number 2, 4, 5 and 9, as indicated by the circles. Examining the basic data, it can be seen that DMU 5 has the second-highest weighted sum of complicating factors. Probably due to this, the value of the efficiency score increased to 100% when including the complicating factors. It can also be seen, that DMU 15 is efficient in both models.

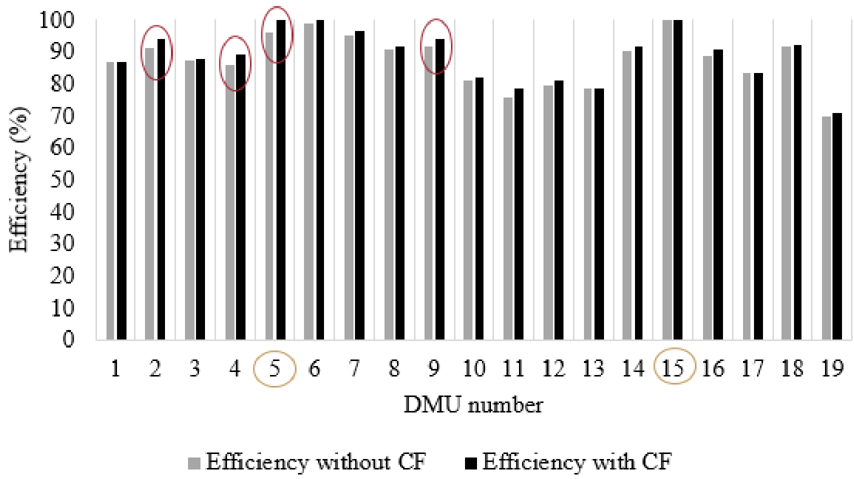

Figure 1. Effect of considering complicating factors (CF) on efficiency

The results of the bar graph shown in Figure 2 illustrates the effect of weighting the complicating factors. Based on the results, it can be noted that on average there is no efficiency change associated with weighting, but in one case (DMU 12) the inclusion of weights results in an apparent efficiency deterioration. This may be due to the fact that although a large number of complicating factors are handled by that county directorate, their workload is not as significant as in the other offices. DMUs 5 and 15 hold their leadership positions with and without weighting as well.

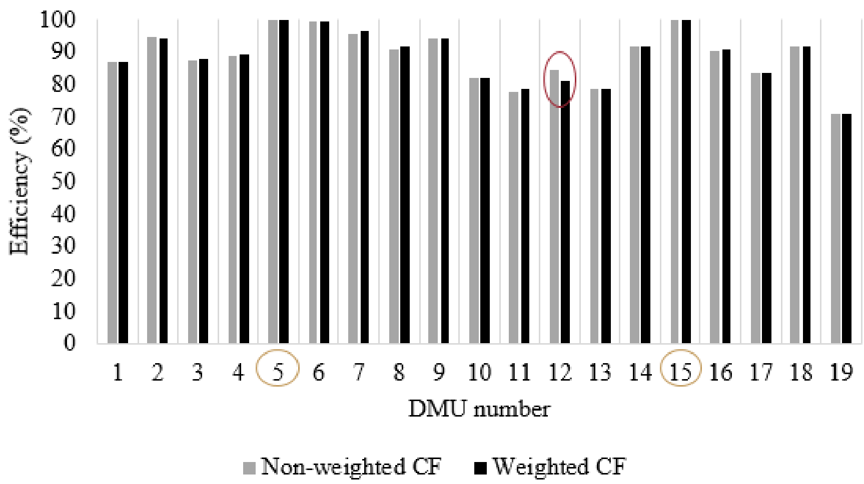

Figure 2. The effect of complicating factors-weighting on the value of the efficiency score

Finally, the weighted complicating factor version model was used for formulating the final recommendations. Although, the weights of the complicating factors don't have a significant effect on efficiency, nevertheless, they increased the acceptance of the results by the HST management. They thought that weights provided a feeling of justice when evaluating the work of employees. The recommendation of employee reallocation based on efficiency results is summarised in Table 2.

The first column of Table 2 shows the number of DMU, and the second column shows the corresponding calculated efficiency score in percentage form. Since an input-oriented model is applied, these values indicate what percentage of the existing workforce is required for the efficient operation of the county directorates. The efficiency score formulates a specific efficiency improvement measure: based on the number of items accounted by the county directorates, it is worth reducing the number of accountants to the extent corresponding to the indicator. The third column of the table shows the full-time equivalent (FTE) of the actual workforce, and the fourth column shows the efficiency-multiplied value of it. If county directorates performed their payroll accounting tasks with such number of employees, they would operate efficiently. The value of the proposed headcount change based on the DEA results is included in the last column.

Table 2. Proposal using annual aggregated data

DMU number	Efficiency score (%)	Actual headcount (FTE)	Proposed (optimal) headcount (FTE)	Proposed change in the headcount (FTE)
1	86.7552	2609.2	2263.62	-345.58
2	94.1121	651.47	613.11	-38.36
3	87.9207	446.17	392.28	-53.89
4	89.4594	554.92	496.43	-58.49
5	**100**	**821.82**	**821.82**	**0.00**
6	99.8401	404.39	403.74	-0.65
7	96.6123	310.86	300.33	-10.53
8	91.9025	344.28	316.40	-27.88
9	93.9825	620.09	582.78	-37.31
10	82.146	416.56	342.19	-74.37
11	78.595	257.41	202.31	-55.10
12	81.2299	339	275.37	-63.63
13	78.7342	657.06	517.33	-139.73
14	91.7369	756.64	694.12	-62.52
15	**100**	**668.64**	**668.64**	**0.00**
16	90.5278	350	316.85	-33.15
17	83.5646	227.29	189.93	-37.36
18	92.1882	294.16	271.18	-22.98
19	71.0731	828.47	588.82	-239.65

The results show that the operation of two county directorates – DMUs 5 and 15 – is considered efficient. It means that these two county directorates used their inputs (payroll accountants) efficiently, while the other county directorates used relatively more workforce than necessary. Efficient operation in this case also means that these two DMUs can serve as a benchmark for inefficient units. By studying and following the strategy and best practices of DMUs 5 and 15, other DMUs can also become better performing. In the case of DMU 6, the proposed headcount change is very small (-0.65). From a practical point of view, this county directorate can also be considered one of the best performers.

The three least efficient DMUs are number 19 (71.07%), number 11 (78.59%) and number 13 (78.73%). The 71.07% efficiency score of DMU 19 indicates to this unit that the employed 828.47 FTE staff is large relative to the amount of work. However, by reducing the workforce to 71.07%, the resulting 588.82 FTE would lead to efficient operation.

The above headcount reduction proposal is based on purely mathematical principles. In human resource management decision-making, however, it is also necessary to take into account the subjective factors of the county directorates, such as the work experience and individual capacity of the employees. If the decision-maker feels the need for a comparison based on objective data analysis – as in this case the leaders of the HST – the results of DEA can excellently serve this objective.

4.2 Analyses based on monthly data

The dynamics of the individual efficiency change of the county directorates were analysed using the monthly input and output values (see the detailed results in Annex 1). When analysing the monthly data, we first examined how the efficiency scores of the 19 DMUs developed in each month.

During the period under review, there was only one case where only one DMU proved efficient: in the 5th month, no county directorate other than DMU 5 functioned efficiently. In eight cases, we can talk about efficient pairs, i.e., there are eight months in which two DMUs achieved 100% efficiency. In these months, it's interesting to observe that one of the pair always consists of either DMU 5 or DMU 15. In addition, in three months (3rd, 8th, and 9th) three DMUs proved efficient at the same time.

Examining the performance of the least efficient county directorates previously determined on the annual basis, it can be observed that DMU 19 ranks last in order of efficiency in all but one month (3rd month). DMU 11, on the other hand, shows fluctuating performance: it is mostly among the least efficient DMUs but enters the midfield based on its performance in a couple of months. DMU 13, similar to number 19, also produces stably low efficiencies.

Based on the monthly data, we also examined how the relative efficiency of each county directorate changes over time. Figure 3 exhibits the pattern of DMUs with some interesting efficiency trends.

- DMU 1 shows fluctuating performance, cyclicality can be observed: efficiency deteriorates and improves every 2-3 months.
- It is also interesting to observe the fluctuation in the performance of DMU 9. Except for one month, the direction of efficiency change is different in each month - after increasing, it decreases and then increases again.
- At DMU 10, the value of the efficiency score is between 77% and 87%, showing a decreasing trend.
- The efficiency of DMU 12 is around 80%, but an extreme value is found in the 9th month indicating an extra workload in this period.
- In the case of DMU 18, a steady increase can be seen where the directorate has finally reached 100% efficiency.
- Finally, at DMU 19, an outstanding value can be found in the 3rd month: the efficiency score is 82%, while its average value is 70%.

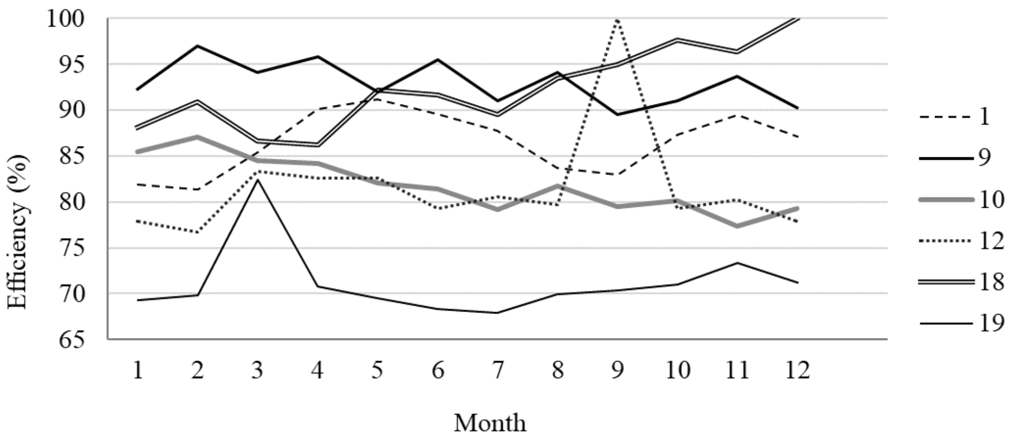

Figure 3. Efficiency function of some DMUs with characteristic trends

Fluctuations in the outputs may stand behind the above patterns. Outstanding values may indicate that the given county directorate handled more than the average number of accounted items in a given month, thus, an otherwise inefficient (larger) headcount became justified in those months. For example, in the case of DMU 12, the results suggest that in the ninth month, all staff were needed to efficiently handle the tasks assigned to them, while in other months, a smaller headcount would be sufficient to perform the activities.

Based on monthly analyses, however, it is not advisable to develop a workforce allocation strategy, as payroll accounting staff are not present as a temporary capacity in the operation of the HST. In addition, the monthly fluctuation of the number of accounted items may be due to a number of external impacts that cannot be influenced but the county directorates can only adjust to them. Such external factors include, but are not limited to, varying levels of emigration in counties, changes in employee health status (e.g., pregnancy, long-term illness, sick leave), but changes in legislation and the political environment also affect labour allocation practices.

With the analysis based on the monthly data, we intended to confirm the proposals made in the previous subchapter. The results supported the conclusions obtained using the annual data, with county directorates 5 and 15 to be considered as benchmark units.

5. Generalization of the applied method

The study performed in the framework of the current research can be generalized and regularly repeated for new study periods. In this case, defining the input and output data for the new assessment period and setting some basic parameters are new tasks to perform. The suggested steps for re-conducting the research are as follows:

- Step 1: Deciding the type of DEA model used, defining the purpose of the comparison;
- Step 2: Deciding the elements of the model (DMUs, inputs and outputs), data collection;
- Step 3: Calculating the results of the relative efficiency analysis: given that linear programming models need to be solved to calculate the efficiency score, it is recommended to use a special DEA software (e.g. PIM-DEA) or other linear programming solvers;
- Step 4: Managerial analysis of the preliminary results, possible correction and completion of the data;
- Step 5: Repeating the calculations and finalizing the results;
- Step 6: Drawing conclusions and making managerial decisions.

The obtained results can be the basis for the reallocation of tasks, staff change decisions and changes in the applied payroll accounting technology. However, it can often reinforce best practices. It may also be necessary to review certain conditions and parameters if the performance analysis is performed regularly. The selection of input and output factors must always be revised, because technological change may introduce new elements both on the input and on the output side. Furthermore, the continuous monitoring and updating of data are essential.

6. Conclusion

In summary, in the presented research, a relative efficiency analysis among the county directorates dealing with payroll accounting at the Hungarian State Treasury with the help of an input-oriented CRS approach radial DEA model was performed. The number of accountants employed in each county directorate as an input factor, while the weighted sum of accounted items and the weighted sum of complicating factors were the basis for comparison.

We identified efficiently functioning county directorates and made a numerical proposal on the number of employees in inefficient units. It is important to emphasize that inefficient operation can be due to several external reasons, it is not necessarily due to a lack of work allocation or organization. Efficiency can be influenced by the legal and labour constraints of the headcount change, the peculiarities of the division of tasks, as well as numerous local circumstances influencing the tasks, which are not reflected in the data used for the analysis. When exploring efficiency improvement opportunities, it is recommended to examine these local characteristics alongside with the numerical data as well.

Based on the results, it can be concluded that most of the county directorates examined are inefficient and overstaffed. Assuming constant returns to scale, increasing inputs results in a proportionally equal output increase. However, this is not necessarily true in real operations, and staff allocation decisions must be made taking into account the different abilities and experience of employees. Furthermore, it is important to emphasize that the DMUs studied are only efficient or inefficient relatively to each other. Thus, it is possible to operate better than the efficient DMU, but further information is necessary about the technologies and operational practices at other units which are outside of the set of examined DMUs.

When analysing the effect of complicating factors, we showed that an increase in efficiency can be observed for more county directorates as a result of considering these factors. Therefore, it is worth keeping this good practice, it is advisable to continue to measure and evaluate the impact of these factors. However, the weighting of complicating factors proved to be a negligible operation, and no significant efficiency change was caused by taking the weights into account.

Finally, reflecting on the monthly efficiency analysis, we would like to confirm that it is not possible to draw appropriate conclusions from the analysis of short-term data. A long-term strategy can only be created based on a data set for larger periods. Furthermore, in addition to objective indicators, subjective evaluation should be used in decisions related to workforce management.

The presented analysis was based on objective mathematical relationships and the use of linear programming models. However, the development of the applied mathematical model required a number of subjective decisions and assumptions (by both authors and data providers) that may limit the general applicability of the results. At the same time, the results of the research can justify a number of operational changes that can be implemented directly in practice: the results can shed light on the causes of inefficient operation, help to rethink aspects related to the division of tasks and/or headcount management and provide information on the organizational and technological development of payroll accounting. In order to make a proposal that can be applied in general practice, the study contains the steps required to repeat the research.

The results of the study raise a number of theoretical questions in addition to solving efficiency problems. The weighting of payroll tasks necessitates the examination of accuracy problems of the applied parameters by means of sensitivity analysis. In addition, some non-discretional environmental factors highlight the theoretical difficulty of taking into account disadvantageous or advantageous operating conditions. These problems provide challenging questions for further theoretical and applied research as well.

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Új Nemzeti Kiválóság Program

Innovációs és Technológiai Minisztérium

Annex 1

Table of the 12-month efficiency scores of the 19 examined DMUs – the values in the inner cells of the table indicate the efficiency of the given DMU in the given month in the form of percentages (%).

Month/ DMU	1	2	3	4	5	6	7	8	9	10	11	12
1	81.94	81.35	85.42	90.11	91.15	89.59	87.74	83.70	83.02	87.34	89.51	87.18
2	93.65	90.72	93.21	93.49	92.92	97.17	92.49	100.00	100.00	92.50	94.31	92.60
3	88.15	84.99	87.16	88.77	88.48	88.62	89.41	85.85	83.14	85.11	88.06	88.56
4	87.34	92.27	89.98	88.49	89.20	90.35	86.83	94.38	91.25	92.24	91.37	89.77
5	100.00	96.37	100.00	100.00	100.00	97.36	96.08	98.55	99.34	98.93	100.00	100.00
6	99.30	100.00	100.00	100.00	97.57	100.00	99.32	100.00	97.33	98.57	100.00	96.63
7	94.57	95.00	97.05	93.08	93.59	98.16	100.00	97.74	97.58	100.00	98.41	91.67
8	97.93	97.33	94.53	87.21	87.87	95.74	93.71	91.44	91.10	89.55	91.45	87.90
9	92.30	96.99	94.11	95.82	91.96	95.46	91.01	94.13	89.58	90.98	93.71	90.33
10	85.45	87.12	84.47	84.23	82.07	81.38	79.15	81.77	79.45	80.11	77.34	79.24
11	79.08	81.05	74.83	78.18	75.13	80.65	77.99	84.97	87.07	85.12	80.81	80.87
12	77.91	76.70	83.34	82.64	82.65	79.28	80.53	79.69	100.00	79.25	80.23	77.85
13	77.12	75.69	77.86	78.26	79.72	78.05	79.17	80.01	78.93	79.11	79.10	75.80
14	86.19	86.05	92.46	92.03	95.91	90.99	88.37	89.95	87.65	90.82	97.31	96.07
15	100.00	100.00	100.00	97.84	97.09	100.00	100.00	100.00	100.00	100.00	99.36	95.55
16	90.59	88.75	91.01	90.97	89.33	90.68	87.11	95.73	90.27	91.10	91.06	85.00
17	86.85	87.25	87.03	83.67	83.42	83.08	82.00	80.70	79.38	81.02	81.68	81.43
18	88.19	90.95	86.69	86.26	92.19	91.63	89.48	93.52	94.94	97.64	96.39	100.00
19	69.30	69.84	82.41	70.76	69.57	68.31	67.92	69.95	70.36	70.98	73.33	71.21