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Financial performance–efficiency nexus in public health services: A nonparametric evidence-based approach

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ABSTRACT

Public health services, as a preventive aspect of health care, are essential for the sustainability of the entire health care system. However, the context of public health services, which focus is primarily on prevention, is not a common setting when measuring the efficiency within nonparametric evidence-based approach. The aim of this study is to measure the efficiency of the financial performance of organizational units of the public health institute in Croatia, the Health Ecology Department in particular, during the period 2016–2018 using data envelopment analysis. Among the many reasons behind choosing this nonparametric method is the fact that it identifies the sources of inefficiency and specifies the directions and magnitudes of improvements required. Two input-oriented models – CCR under constant and BCC under variable returns-to-scale assumption – are employed for evaluating three types of efficiency – technical, pure technical and scale efficiency. Two hypotheses are examined and empirically confirmed: first, that there is significant between-unit variability in financial performance, and second, that investments are the major source of inefficiency among the observed indicators. The results have additionally revealed that the mentioned differences are less pronounced in the case of pure technical efficiency, implying that the overall inefficiency of the Health Ecology Department units can be generally attributed to scale efficiency. Besides, only three out of twelve department units are considered efficient. The implications of the research results are aimed at further research and testing the efficiency of the entire network of public health institutes, as well as to provide policy makers with new insights when considering different modes of organizing and delivering public health services.

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1. Introduction

Public health as “the science and art of preventing disease, prolonging life and promoting health through the organized efforts of society” (Acheson, 1988; based on Winslow, 1920) is the determinant of a developed and effective health system. It is important to note that public health is a preventive aspect of health care, not curative, and that it covers health care at the community level, not the individual. As such, the development of the society is linked to the development of the public health system, i.e. the readiness of the state to provide its programs and tasks in an efficient and effective way with the purpose of protecting and improving health.

Therefore, the economic evaluation of certain measures and activities of the public health system is of crucial importance, and pursuit of efficiency is one of the central preoccupations of health policy makers and managers. The concept of health sector efficiency and effectiveness is the most discussed dimension of health care performance aiming to capture the extent to which the inputs expressed financially or non-financially are used to secure valued health system goals. Efficiency becomes particularly important from the aspect of financial pressures and concerns over long-term financial sustainability experienced in many health systems as decision-makers seek to ensure that available health care resources are used efficiently for the proclaimed health benefits.

When it comes to measuring the performance of public sector units in general, existing literature emphasizes that it is a challenging undertaking, due to the problem of both conceptual and technical nature. The current literature highlights the following as the main measurement problems in the public sector (Kattel et al., 2013): 1) the diverse nature of public sector services, the wide range of users, and the difficulty in defining the goals; 2) the set objectives and expected public sector effects do not follow the single criterion of profit making and 3) many methods for assessing economic impact are almost impossible to apply to the public sector because they require monetization of the effects (e.g. intangible effects, such as improved health, quality of life, etc.).

The concept of efficiency defines the maximum level of output that can be obtained by using the same level of inputs in the production, i.e., the operating process. Generally, a distinction can be made between technical efficiency (the appropriate use of resources, meaning achieving the maximum output from the minimum quantity of input) and allocative efficiency (the appropriate proportion of resources used taking into account the price, implying how different resource inputs are combined to produce a mix of different outputs). Overall efficiency reflects the combined effect of allocative and technical efficiency. In this paper, the focus is on measuring the (global) technical efficiency, (local) pure technical efficiency, and scale efficiency in providing public health services, i.e. part of the services provided by public health institutes, specifically health ecology services, which are insufficiently covered by empirical research, unlike the dominant hospital settings (Kohl et al., 2019; Hollingsworth, 2008). Nevertheless, the importance of the health ecology is not questionable. Moreover, the ecosystems i.e. the environment has been recognized as the fundamental health influencing factor (Jackson & Kochtitzky, 2001, and Barton & Tsourou, 2000, cited in Coutts, 2010, pp. 53). As emphasized by Bulog (2018), health

ecology is a “science that in its methodological approaches and methods encompasses professional and scientific research focused on certain aspects of human health, including quality of life, determined by the interaction of physical, chemical, biological, and social factors in the environment”. Although, researchers (Kolda et al., 2019; Kelava et al., 2018; Marić et al., 2018), note that public health institutes in general, and health ecology in particular, is important in the sense of scientific research of domestic health and environmental improvements, Steingraber and Hill (2002) emphasize on the disadvantages of contemporary health models, and health and ecology professionals. Hence, they claim that health models frequently ignore ecological dimensions of human health and disease, and that the professionals are not trained to engaging with communities in order to understand the ability of the environments health benefits maximization. Likewise, Andrews (2018) points out professionals of the built environment, health sciences and ecology fields recognizing those limitations and calling for collaborative approaches across disciplines and stakeholders. This coincides with the earlier theory of health ecology. Although, many frameworks, including the Coutts (2010) Public Health Ecology framework, have been developed through the years, it seems that they were also mostly made to provide public health and environmental professionals to understand each other’s work and its connections (Jennings et al., 2019). Hence, Honari (1999, pp. 2) saw health ecology as a “lifelong struggle to find a concept and framework with the capacity to encompass many disciplines that are themselves complex and multi-dimensional”, formed foremost because of the interdependence and inter-relationship of health and environment. According to all mentioned, increased research is needed in this area of public health.

In the context of the public health service sector, efficiency can generally be expressed as the ratio between a certain output (the result of public health activities efforts) and resources used to generate it. One of the main goals pursued by most governments is to improve their health system both in terms of efficiency and quality of services, i.e., to ensure that its resources are put to good use. Although public health services in most European countries are mostly budget-funded, exceptions are ecological public services that also provide a large share of their services on the market, i.e. they are faced with competitive pressures in a segment of their activity. The efficiency of the Health Ecology Department (HED) of the one public health institute in Croatia, that has been chosen as the subject of this research, will be evaluated using the nonparametric evidence-based approach, i.e. data envelopment analysis (DEA) as one of the most promising techniques to aid the improvement of public health services’ efficiency. Although in some parts their business activities are inter-dependent, each of a total of 12 units within the observed department has its particular function, and because of the variety of inputs and outputs, it is difficult to choose the ones that are comparable in the sense of making a conclusion on the efficiency of the units. Generally, DEA does not require the units in which the indicators are expressed to be congruent, but it is not uncommon. Considering the fact that the department, i.e. units are dependent on their own income achievements in addition to state and county funding, and that the big difference in business performance between them has become an increasing concern to the management, the first requirement is to conduct a financial perspective analysis. As stated by the National

Health Care Strategy 2012-2020 (2012), it is not enough just to find additional funding sources; it is crucial to organize a method of collection and appropriate allocation. Moreover, it is necessary to increase financial discipline by strengthening the connection to the measurable performance indicators (National Health Care Strategy, 2012). Hence, more efficient management of financial resources in healthcare is one of the four main goals of the Strategic Plan of the Ministry of Health for 2020–2022 (2019). Therefore, the research in this paper aims to evaluate efficiency based on financial inputs and outputs, i.e., the efficiency of financial performance of preventive public health services provided by the chosen HED. Implications of the results of the conducted empirical research are aimed at providing policy makers and the management of the public health institutes more research based data and information when considering the modalities of an effective institutional form of providing public health services. In this context, two hypotheses are formulated and will be tested. While the first one proposes a significant between-unit variability in financial performance, the second one highlights investments as a major source of inefficiency among the selected indicators.

The paper is structured as follows: after the introduction, the first section presents the review of literature on public health services' efficiency and the application of DEA as the method on which the analysis is based. The second section provides the methodological and analytical framework of the study. Section three presents the results of the conducted efficiency measurement, followed by the discussion and conclusion with included implications and suggestions for further improvements.

2. Review of literature on public health services' efficiency using data envelopment analysis

The context of public health services under the auspices of the institutes of public health, with the focus primarily on the preventive character of public health services, is not such a common setting in applying DEA. This method is suitable for measuring the productivity and relative efficiency of units that use multiple inputs to produce multiple outputs in the production process with a functional form that does not have to be specified in advance. Precisely this feature makes this technique suitable for use in measuring the performance of public sector entities (Kohl et al., 2019; Carrillo & Jorge, 2017; Liu et al., 2016; Alonso et al., 2015; Asandului et al., 2014; Martini et al., 2014; McGlynn, 2008; Gattoufi et al., 2004). When considering its application as a technique for efficiency estimation, according to Liu et al. (2013), the top five branches of DEA applications are banking, healthcare, agriculture & farming, transportation, and education. With regard to the healthcare domain, the most widespread use of the DEA method is in the hospital setting (Kohl et al., 2019; Nistor et al., 2017; Kaitelidou et al., 2016; Gholami et al., 2015; Martini et al., 2014; Hollingsworth, 2008; Sherman, 1984). Other units included in the analysis of healthcare efficiency include complete healthcare system at the national level (Asandului et al., 2015; Asandului et al., 2014; Adang & Borm, 2007), healthcare system at the level of individual regions within a country (Stefko et al., 2018; Carrillo & Jorge,

2017; De Nicola et al., 2011; Nuti et al., 2011) or specific healthcare units, for example intensive care units, dialysis centers, nursing homes, etc. (Mitropoulos et al., 2016; Garavaglia et al., 2011; Tsekouras et al., 2010; Nunamaker, 1983).

According to CDCs (Centers for Disease Control & Prevention, 2014), public health consists of ten essential services crucial for the achievement of social determinants of health, including health literacy and access, community and social cohesion, environmental conditions and housing quality, etc. In the sense of interventions relating to the environment health, the most important service is health ecology, which is the basis of this study. Nowadays, environmental threats have a worldwide long-term effect on the biological system, its diversity and, of course, human health. According to the findings of Prüss-Ustün et al. (2016), 23% of global deaths and 26% of deaths among children under the age of five are caused by modifiable environmental factors. Therefore, public health services have been formed in order to prevent disease, i.e. ensure people's health through a healthy environment. Thus, their main goal is to preserve and improve the populations' health outcomes through the achievement of the objectives of disease prevention and the health consequences of man-made catastrophes, natural and environmental hazards (Park et al., 2017).

According to current knowledge, efficiency evaluation of public health services, other than those provided by hospitals, primarily preventive public health services, such as services provided by public health institutes, are not represented in the existing empirical research, except for the research carried out by Vitezić et al. (2016). They conducted empirical research of 12 units within an institute of public health services in Croatia in the period of two years, 2014 and 2015, in order to explore and analyze the suitability of DEA for the measurement of the efficiency of a range of different services offered by institutes of public health in Croatia. In their study they opted for an input-oriented model with the assumption of variable returns to scale, named the BCC model after its authors Banker, Charnes and Cooper (Banker et al., 1984), and conducted two models with a different selection of inputs and outputs. For the first model they used employees' salary, direct cost, and investments as inputs, and total revenue as the output. The second model included total costs and number of samples as inputs, while the number of analyses and total revenues were selected as outputs. The results showed a tendency of decreasing the average efficiency in both models, which was a good starting point for the analysis of the reasons for decreased management efficiency, and according to the authors, a prerequisite for implementing the Balanced Scorecard (BSC) as an effective tool for a performance management system.

Most DEA models in the existing research analyses of public health efficiency are either input- or output-oriented and include either constant returns to scale (CRS) or variable returns to scale (VRS). Kohl et al. (2019) provided an overview of the DEA models which have been applied to healthcare with a focus on hospitals from 2005 until the end of 2016. The CCR model, named after its authors Charnes, Cooper and Rhodes (Charnes et al., 1978) and based on the assumption of CRS, and the previously mentioned BCC model with VRS are still the most frequently used models in measuring the efficiency in the healthcare sector (Kohl et al., 2019). According to their study, almost 80% of the included research studies apply one of the two basic models.

The vast majority of studies in the reviewed literature is mainly focused on the US, Asia, countries of northern and western Europe, with the exception of Greece, and Africa (Kohl et al., 2019; Nuti et al., 2011), while only a few empirical studies have analyzed the efficiency of healthcare services in Croatia (Vitezić et al., 2016; Rabar 2013; Rabar, 2010).

3. Analytical and methodological framework

The Croatian public health service sector is organized through one national and twenty one county-level institutes, including three teaching institutes. One of them is the Teaching Institute of Public Health of the County of Primorje-Gorski Kotar, which is the basis of this study. Although the Institute consists of six main health service organizational departments (Health Ecology, Epidemiology, Mental Health and Addiction Prevention, Microbiology, School and Adolescent Medicine, and Social Medicine), the most profitable and the most market-oriented one is the HED. Given the fact that the institutes are mainly financed from the state and county budget funds, departments and units that contribute to additional, i.e. own income are crucial for the overall efficiency achievements of institutes. Therefore, this research focuses specifically on the efficiency of financial performance of the HED. Besides, the HED has the most important role when it comes to sustainability and health prevention of the residents of the county and wider, and is therefore considered a significant benchmark. Hence, as noted by Park et al. (2017), public health services ensure people's health primarily through a healthy environment. Only through constant monitoring and analysis of environmental factors can health improvements and sustainable development be achieved.

After an in-depth literature review, and for the purpose of achieving the set goal, the study was carried out in the two following phases: 1) financial data provided by the controlling department of the institute were analytically processed through the DEA, and 2) an interview with the deputy director, i.e. the head of HED, was conducted in order to gain the management perspective of the obtained results.

3.1. Decision-making units

As mentioned before, the basis of this study is the HED, the efficiency of financial performance of their services in particular. The main task of the department is to carry out measures of human health protection (monitoring, evaluation, prevention, and correction) related to environmental factors with potentially harmful effects (chemical, biological, physical, etc.) that come into contact with people, like air, water, soil, etc. In addition, staff members as experts in their field of activity also participate in the creation of public health policies. In order to achieve its mission of preserving and promoting the health of all residents and visitors of its county, and wider, through the protection of all environmental components, HED is organized through twelve units (Table 1). Although every department has its own function, they are interdependent when it comes to the fulfilment of the overall health service prevention task.

As revealed by its very name, DQOA is mainly responsible for continuous air pollution (immission) testing. DD&NW performs the testing of the safety of water for human consumption, water quality in nature (sea on beaches, natural mineral and spring water, etc.) and table waters, as well as the quality of water for swimming pools, and other types according to customer requirements, while DW&WW is responsible for the determination of physical, physicochemical, chemical, and biological indicators of wastewater, chemical analysis and categorization of waste for disposal in a safe manner, and the analysis of the specification and classification of solid recovered fuel. DFC's activities are focused on the control and assessment of food safety and quality (pesticides, mycotoxins, metals and metalloids, etc.) in the production and trade and materials and items coming into direct contact with them. The primary role of DIN is to monitor the influence of people's nutrition (children of preschool and school age, young people and the elderly) on health for timely detection of disorders or nutritional deficits that may cause chronic diseases. DPEF examines the chemical, physical and biological factors in the working environment (estimation of safety, temperature, relative humidity, illumination, vibration, etc.). DAE deals with the measurement of pollutant emissions from stationary sources, while DME performs microbiological analysis of food hygiene, consumer goods, production facilities, indoor air, and water. DCAT conducts chemical analysis by instrumental spectrometry and chromatography in terms of food and the environment. DBM&E carries out biological and chemical monitoring activities of the marine environment, pollen analysis of honey, and concentration of pollen allergens in the air. It also creates pollen calendars and performs toxicity tests. DECTX also carries out toxicity tests, but aquatic ones. Furthermore, it is responsible for monitoring immune change and biomonitoring of the county residents, as well as their exposure to toxic compounds. Besides, it monitors changes in marine organisms and performs chlorophyll concentration tests for the sea and groundwater. Last, but not least, DSES deals with specialized sampling and field physical-chemical analyses of water and sediments. As evident from the descriptions of each unit, i.e. department, the task and responsibilities are interrelated, and are therefore equally important when analyzing the efficiency of the entire department. Therefore, all twelve HED units represent the decision-making units (DMUs) of this research conducted using the DEA.

Table 1. The names and abbreviations of HED's units.

No.	Name	Abbreviation
1	Department for quality control of outdoor air	DQOA
2	Department for control of drinking water and water in nature	DD&NW
3	Department of waste and waste water control	DW&WW
4	Department of food control	DFC
5	Department of improving nutrition	DIN
6	Department for control of physical environmental factors	DPEF
7	Department for control of air emissions	DAE
8	Department of microbiology environment	DME
9	Department of common analytical techniques	DCAT
10	Department of biological monitoring and exposure	DBM&E
11	Department of ecotoxicology	DECTX
12	Department for sampling of environmental samples	DSES

Source: Own research.

3.2. Data envelopment analysis: the concept and basic models

DEA is a non-parametric mathematical programming approach for assessing the relative performance of a group of entities/decision-making units based on a common set of indicators/variables that are partitioned into inputs and outputs. In order to improve the efficiency, the inputs are preferred to be as small as possible and the outputs to be as large as possible. The calculation is performed by including their empirical data into a linear program that represents the DEA model and results in a single relative performance efficiency index. Depending on management preferences, the formulation of the model can be input- or output-oriented (or non-oriented, which is applied much less frequently). The specific model formulation also depends on the assumption of returns to scale, which in some cases may be indicated by a preliminary investigation of properties of the process being analyzed. If this does not ensure reliable information on returns to scale, it will be provided based on the significance of the differences of the results obtained by the models under both CRS and VRS assumptions.

Regardless of the assumed returns to scale and the model orientation, the production possibility frontier is formed by enveloping inputs from below and outputs from above. Consequently, the DMUs on this 'best practice' frontier, in contrast to the rest of the observed DMUs, are considered efficient (i.e. benchmarks) and are all assigned the best efficiency measure of 1 (or 100%). The efficiency scores of the non-frontier DMUs are between zero and one, depending on their distance from this efficient frontier. This inefficiency is a result of using excessive inputs at a given output level and/or producing poor output at a given input level, and can be eliminated by catching up a model-calculated best-practice frontier projection point. Given that it is empirically created, this frontier represents a practically achievable target for each inefficient DMU, also serving as a basis for identifying and quantifying its inefficiency sources and their amounts, improvement directions and reference DMUs to be most directly compared with.

A major factor in the selection of this technique over traditional benchmarking methods for this analysis was its ability of dynamic efficiency measurement, without the necessity of explicitly specifying the functional relationship among the variables and/or predetermining their weights. Furthermore, the weights are calculated by the model itself in order to maximize the efficiency score for each evaluated entity, thus avoiding the subjective judgement of each weight's significance.

Despite its many advantages, it should be mentioned that, from an empirical point of view, DEA has several disadvantages. As in statistics or other empirically oriented methodologies, there is a problem involving degrees of freedom, which is compounded in DEA because of its orientation to relative efficiency. In the envelopment model described later, the number of degrees of freedom will increase with the number of DMUs and decrease with the number of inputs and outputs. A rough rule of thumb which can provide guidance is given by $n \geq \max \{m \times s, 3(m + s)\}$, where n = number of DMUs, m = number of inputs and s = number of outputs (Cooper et al., 2006; for a more detailed discussion on the size of the data set, see Sarkis, 2007). An additional shortcoming is the fact that, unlike multi-criteria approaches that are most commonly applied to ex-ante problems where data are not available at

the moment, DEA enables an ex-post analysis of the past to learn from (Adler et al., 2002).

3.3. Indicators and model specification

Annual data for the three-year period 2016–2018, provided by the Department of Controlling of the Institute, were used for the efficiency measurement of the HED's units within the Teaching Institute of Public Health of the County of Primorje-Gorski Kotar. As it is a prerequisite by the DEA, all selected data, i.e. inputs and outputs are comparable and reliable for the entire HED. Thus, the following indicators were selected and will be integrated into an unique efficiency measure:

- salaries,
 - direct costs, and
 - investments
- as input variables, and
- total revenues
- as the single output variable.

With twelve DMUs, three inputs and one output, the aforementioned rule-of-thumb requirement is fulfilled.

Although the chosen indicators match with those that Vitezić et al. (2016) used in one of their models, this study is a follow-up providing new and additional criteria. Firstly, it is based upon a new and longer period of selected input and output indicators. And secondly, it additionally takes into account the CCR model. Hence, the study focuses on the measuring of three types of efficiency – technical, pure technical, and scale efficiency in order to determine whether the cause of inefficiency is in inefficient operation or disadvantageous conditions. Only by identifying the source of inefficiency can appropriate measures and actions be proposed and implemented.

Summary statistics for the used sample, aggregated over time and across units, is reported in Table 2. The summary data show great variability, which makes it impossible to draw firm conclusions about the average performance of the units in a particular year. Obviously, the conclusion is highly dependent on the selected statistical measure. This is explained by the following example. Compared to 2017 and 2018, the year 2016 is characterized by the lowest minimum values of all three inputs. Since smaller quantities of inputs are desirable, this in itself would make this year relatively the most successful one. At the same time, however, that year is characterized by the highest maximum values of two inputs, as well as by the lowest maximum output value, which is both undesirable and would mean that this was the worst year. The actual result is obviously somewhere in between, as evidenced by the average values of the variables which for this year, depending on the observed indicator, range from the most favorable (lowest average salaries) to the least favorable (highest average investments and lowest average total revenues). Nevertheless, the DEA will, among other things, address the question which year is the most and which is the least successful, i.e., rank their success.

Although correlations of the pairs of selected indicators are not the direct subject of this study, the extremely strong positive relationship between average salaries and average total revenues (0.9999) is worth considering as an objective and thought-provoking justification for changes in wage policy.

The initial phase of the analysis reported in the next section revealed great diversity among the results obtained from the CCR and BCC models (Table 3), that can be attributed to the return effect with respect to the range of units' activities. This can be considered a confirmation of greater suitability of the BCC than the CCR model for the process analyzed in this paper. However, since one of the aims of this study is to single out different types of inefficiency, both CCR and BCC models were used. The models are input-oriented, meaning that they minimize input for a given level of output.

The formulation of the models under consideration is extensively described in Cooper et al. (2006). A brief summary: let there be n homogenous DMUs, characterized by m inputs and s outputs. The data set is decomposed into the matrix of inputs ($X = (x_{ij}) \in \mathbb{R}^{m \times n}$), and the matrix of outputs ($Y = (y_{rj}) \in \mathbb{R}^{s \times n}$). The input-oriented models estimate the relative efficiency of DMU_o , $o \in \{1, 2, \dots, n\}$, by solving the following linear program(s) (envelopment form):

Table 2. Data summary statistics, 2016–2018, in Croatian kunas.

Variable		Year	Mean	Median	SD	Min.	Max.	CV (%)
Inputs	Salaries	2016	713,904	648,955	362,598	228,652	1,397,621	50.79
		2017	829,937	792,650	423,673	230,766	1,464,912	51.05
		2018	916,846	815,509	442,032	379,527	1,693,619	48.21
		2016-2018	820,229	763,661	419,167	228,652	1,693,619	51.10
	Direct costs	2016	490,287	304,132	446,010	60,616	1,430,618	90.97
		2017	507,314	340,013	415,941	72,386	1,352,905	81.99
		2018	467,137	363,728	370,638	120,432	1,353,355	79.34
		2016-2018	488,246	326,047	412,358	60,616	1,430,618	84.46
	Investments	2016	394,268	152,541	634,766	3,486	2,279,647	161.00
		2017	153,527	102,415	131,632	29,262	443,032	85.74
		2018	185,538	142,092	130,561	25,496	406,572	70.37
		2016-2018	244,444	138,842	396,436	3,486	2,279,647	162.18
Output	Total revenues	2016	1,265,457	233,884	1,631,746	9,883	5,012,667	128.95
		2017	1,343,977	319,070	1,816,363	2,949	5,778,964	135.15
		2018	1,399,595	405,248	1,782,744	9,381	5,616,635	127.38
		2016-2018	1,336,343	327,910	1,746,333	2,949	5,778,964	130.68

Note: SD = standard deviation; CV = coefficient of variation.

Source: authors' calculations.

Table 3. Summary statistics for the input-oriented CCR and BCC models.

Results of the pre-analysis	CCR model			BCC model		
	2016	2017	2018	2016	2017	2018
Year						
Number of efficient units	2	1	3	6	3	6
Number of inefficient units	10	11	9	6	9	6
Average efficiency score	0.4435	0.4321	0.4388	0.8021	0.7170	0.8077
Standard deviation	0.3517	0.3686	0.3929	0.2631	0.2589	0.2454
Minimum efficiency score	0.0111	0.0057	0.0040	0.1709	0.1795	0.2575
Number of units with below average efficiency	7	7	8	4	6	5

Source: Authors' work based on DEA-Solver-Pro calculations.

$$\begin{aligned} \min_{\theta, \lambda} \theta \\ \text{subject to } \theta x_o - X\lambda \geq 0 \end{aligned} \quad (1)$$

$$Y\lambda \geq y_o \quad (2)$$

$$\lambda \geq 0 \quad (\text{DEA} - \text{CCR}) \quad (3)$$

$$e\lambda = 1 \quad (\text{DEA} - \text{BCC}) \quad (4)$$

The CCR model measures technical efficiency and is formed by the objective function and its conditions represented by equations (1)-(3). The BCC model measures pure technical efficiency and contains an additional restriction represented by equation (4). The first three conditions consist of m , s and n constraints, respectively. In the analyzed case, m is 3, s is 1 and n is 12. The optimal objective function value θ^* represents the efficiency measure assigned to the considered unit DMU_o and, in the case of its inefficiency, also the input reduction rate ($0 < \theta^* \leq 1$). At the same time, λ is a non-negative column vector corresponding to the proportions contributed by efficient entities to efficient frontier projection of DMU_o , and e is a row vector with all elements equal to 1 (both of them n -dimensional).

This first phase minimizes θ , clearly indicating by the constraints (1) and (2) that $(X\lambda, Y\lambda)$ outperforms (θ^*x_o, y_o) when $\theta^* < 1$. In this context, the input excesses and the output shortfalls are identified as “slack” values and determined by the formulas:

$$s^- = \theta x_o - X\lambda \quad (s^- \in \mathbb{R}^m), \quad (5)$$

$$s^+ = Y\lambda - y_o \quad (s^+ \in \mathbb{R}^s), \quad (6)$$

which are both non-negative for any feasible solution (θ, λ) of the above linear program(s). Potentially remaining input excesses and output shortfalls will be discovered in the second phase by maximizing their sum while keeping $\theta = \theta^*$.

If the optimal solution obtained in this two-phase process is denoted as $(\theta^*, \lambda^*, s^{-*}, s^{+*})$, the DMU_o is (strongly) efficient if and only if the efficiency score satisfies $\theta^* = 1$ and has no slack, (i.e., $s_i^{-*} = 0$, $s_r^{+*} = 0$ for all $i \in \{1, \dots, m\}$ and $r \in \{1, \dots, s\}$). The DMU_o is weakly efficient if and only if $\theta^* = 1$ but $s_i^{-*} \neq 0$ or $s_r^{+*} \neq 0$ for some i and r in some alternate optima. Otherwise, the DMU_o is inefficient and its efficiency can be improved if the input amounts are decreased radially by the factor θ^* and the input excesses recorded in s^{-*} are removed, and if the output amounts are increased by the output shortfalls in s^{+*} . These input and output improvements form the following projection:

$$\hat{x}_o = X\lambda^* = \theta^*x_o - s^{-*}, \quad (7)$$

$$\hat{y}_o = Y\lambda^* = y_o + s^{+*}. \quad (8)$$

The components of vector λ^* are positive if and only if they correspond to the efficient DMUs that form the reference set E_o of the DMU_o , meaning that the above formulas can be expressed as $\hat{x}_o = \sum_{j \in E_o} x_j \lambda_j^*$, $\hat{y}_o = \sum_{j \in E_o} y_j \lambda_j^*$.

The constraint (4) differentiates the BCC from the CCR model and, together with the condition (3), imposes a convexity condition on allowable ways in which the observations for the n DMUs may be combined, thus also differentiating the shapes of their production frontiers. As a practical consequence, the distance from any inefficient DMU to its CCR projection is no less than its distance to its BCC projection. This generally results in lower CCR than BCC scores and makes CCR efficiency harder to achieve. These differences between global and local efficiency scores come as a result of the scale size of DMU. Therefore, scale efficiency is defined with

$$\theta_{scale}^* = \frac{\theta_{CCR}^*}{\theta_{BCC}^*} \quad (9)$$

and its value obviously also lies between zero and unity. Consequently, the efficiency can be decomposed as

$$\theta_{CCR}^* = \theta_{BCC}^* \times \theta_{scale}^*, \quad (10)$$

revealing the sources of inefficiency, i.e., whether the inefficiency is caused by the inefficient operation of the DMU itself (θ_{BCC}^*) or by the disadvantageous conditions under which the DMU is operating (θ_{scale}^*) or by both.

Application of this method provides the answers to the following set of research questions:

- What is the overall financial performance of the HED units?
- What can be said about the efficiency of the considered units?
- How can the leading (efficient) units be mutually distinguished?
- How did the HED evolve over the period 2016-2018?
- What are the main financial aspects that should be improved?

4. Model application in empirical analysis and efficiency measurement of public health services

The relative efficiency of the financial performance of twelve HED units' presented below were obtained using the DEA-Solver-Pro software by Saitech Inc., and further supplemented by the authors' own calculations. The analysis is based on the annual data relating to four financial indicators (salaries, direct costs, investments, and total revenues) covering the three-year period (2016-2018). The models employed are input-oriented, under both CRS and VRS assumptions. The technical, pure technical, and scale efficiency scores, with corresponding ranks and some summary statistics, are reported in Table 4. Such a range of results will provide a more informed and thorough analysis and discussion, and a better understanding of the findings.

Table 4. Relative input-oriented efficiency results for HED's units.

Unit	Technical efficiency (CCR)					Pure technical efficiency (BCC)					Scale efficiency (CCR/BCC)							
	Year					Year					Year							
	2016	2017	2018	Mean (per unit)	Mean-based rank	SD	2016 RTS	2017 RTS	2018 RTS	Mean (per unit)	Mean-based rank	SD	2016	2017	2018	Mean (per unit)	Mean-based rank	SD
DOQA	1	0.7792	1	0.9264	2	0.1041	1 CRS	0.7888 IRS	1 CRS	0.9296	5	0.0996	1	0.9878	1	0.9959	2	0.0057
DD&NW	1	1	1	1	1	0	1 CRS	1 CRS	1 CRS	1	1	0	1	1	1	1	1	0
DW&WW	0.3557	0.2874	0.4101	0.3511	7	0.0502	0.4732 IRS	0.4120 IRS	0.5332 IRS	0.4728	11	0.0495	0.7516	0.6977	0.7692	0.7395	5	0.0304
DFC	0.8862	0.8395	0.8384	0.8547	4	0.0223	1 IRS	0.8904 IRS	0.9640 IRS	0.9515	4	0.0456	0.8862	0.9428	0.8697	0.8995	4	0.0313
DIN	0.4599	0.3699	0.3105	0.3801	6	0.0614	0.8067 IRS	0.6149 IRS	0.6708 IRS	0.6975	9	0.0805	0.5702	0.6016	0.4629	0.5449	6	0.0594
DPEF	0.0248	0.0057	0.0731	0.0345	11	0.0284	1 IRS	1 IRS	1 IRS	1	1	0	0.0248	0.0057	0.0731	0.0345	12	0.0284
DAE	0.2895	0.3035	0.1345	0.2425	8	0.0765	0.9169 IRS	0.6558 IRS	0.7308 IRS	0.7678	8	0.1098	0.3157	0.4628	0.1841	0.3209	8	0.1138
DME	0.6881	0.8996	1	0.8625	3	0.1300	0.7178 IRS	0.9373 IRS	1 CRS	0.8850	7	0.1210	0.9586	0.9597	1	0.9728	3	0.0193
DCAT	0.0111	0.0209	0.0765	0.0362	10	0.0288	0.1709 IRS	0.1795 IRS	0.2575 IRS	0.2026	12	0.0389	0.0651	0.1163	0.2972	0.1596	9	0.0996
DBM&E	0.2459	0.6611	0.4068	0.4379	5	0.1710	1 IRS	1 IRS	1 IRS	1	1	0	0.2459	0.6611	0.4068	0.4379	7	0.1710
DECTX	0.3189	0.0096	0.0114	0.1133	9	0.1454	1 IRS	0.6971 IRS	1 IRS	0.8990	6	0.1428	0.3189	0.0138	0.0114	0.1147	10	0.1444
DSES	0.0426	0.0086	0.0040	0.0184	12	0.0172	0.5394 IRS	0.4280 IRS	0.5362 IRS	0.5012	10	0.0518	0.0789	0.0202	0.0074	0.0355	11	0.0311
Mean (per year)	0.4435	0.4321	0.4388	0.4381			0.8021	0.7170	0.8077	0.7756			0.5180	0.5391	0.5068	0.5213		
Number (%) of units with below average efficiency	7 (58%)	7 (58%)	8 (67%)	8 (67%)			4 (33%)	6 (50%)	5 (42%)	5 (42%)			6 (50%)	5 (42%)	7 (58%)	6 (50%)		
Median	0.3373	0.3367	0.3586	0.3656			0.9584	0.7429	0.9820	0.8920			0.4445	0.6314	0.4348	0.4914		
SD	0.3517	0.3686	0.3929	0.3609			0.2631	0.2589	0.2454	0.2474			0.3705	0.3886	0.3844	0.3726		
Minimum	0.0111	0.0057	0.0040	0.0184			0.1709	0.1795	0.2575	0.2026			0.0248	0.0057	0.0074	0.0345		
Maximum	1	1	1	1			1	1	1	1			1	1	1	1		
CV (%)	79.30	85.30	89.54	82.38			32.81	36.10	30.38	31.90			71.53	72.08	75.85	71.47		
Number (%) of efficient units	2 (17%)	1 (8%)	3 (25%)				6 (50%)	3 (25%)	6 (50%)				2 (17%)	1 (8%)	3 (25%)			
Number (%) of inefficient units	10 (83%)	11 (92%)	9 (75%)				6 (50%)	9 (75%)	6 (50%)				10 (83%)	11 (92%)	9 (75%)			

Note: SD = standard deviation; CV = coefficient of variation; RTS = returns to scale; CRS = constant returns to scale; IRS = increasing returns to scale.

Source: Authors' work based on DEA-Solver-Pro calculations.

The results reveal differences among the performance ratings that are significant at three levels:

- The unit level - when comparing a particular efficiency type for different units in a particular year,
- The year level - when comparing a particular efficiency type for a particular unit in different years,
- The efficiency-type level - when comparing different efficiency types for a particular unit in a particular year.

This, above all, testifies to the great diversity of the sample studied, and is explained below. Average efficiency of most units is below 1, thus indicating some degree of inefficiency for each of them. This means that none of these units was efficient throughout the entire period of observation. The exceptions are DD&NW in both models, and DPEF and DBM&E in the BCC model. Moreover, five of twelve units were continuously purely technically inefficient, and as many as nine exhibited permanent technical- and scale inefficiency. The average technical and pure technical efficiency scores first declined and then increased, while the average scale efficiency scores did exactly the opposite. This testifies to the different average impacts of inefficient operation of units themselves and of disadvantageous conditions under which they operate on inefficiency. Nevertheless, it is interesting to note that different years are the most and least successful for each type of efficiency. According to both models, the units were on average the least efficient in the year 2017, and the most efficient in 2016 according to CCR and in 2018 according to the BCC model. By contrast, the average scale efficiency was on average the highest in 2017 and the lowest in 2018.

The previously mentioned significant between-unit, between-year, and between-efficiency-type variability is reflected in the divergence between minimum and maximum efficiency values and in the standard deviations. These differences are notably lower when considering a particular unit in different years than when considering different units in a particular year. This provides evidence of a relatively balanced units' performance over time and, at the same time, indicates large differences across units and imposes the consideration of their causes. This divergence is less pronounced in the case of pure technical efficiency than in the cases of technical and scale efficiencies, as evidenced by the numbers of units below average efficiency. Based on these findings, however, the first hypothesis proposing a significant between-unit variability in financial performance has been confirmed.

Efficiency ratings of inefficient units allow them to be ranked directly. Efficient units, on the other hand, cannot be ranked immediately because of their maximum score. However, one of the many approaches researchers have suggested to rank an efficient entity is the overall frequency of its occurrences in reference sets of inefficient ones. Thus, as shown in [Figure 1](#), DD&NW should be ranked first due to the highest total frequencies in both models (29 and 14). It is also the only unit that is a reference set member in all three years according to both models and is therefore recognized as a best-practice example within the HED. It should be noted that the

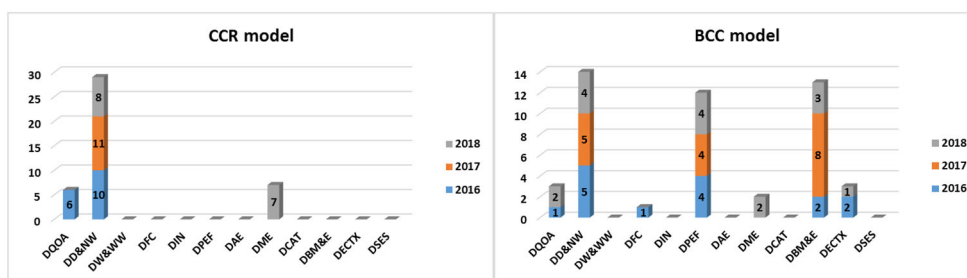


Figure 1. Reference set frequencies.

Source: authors' work based on DEA-Solver-Pro calculations.

Table 5. Inefficiency sources.

	Model	Year	Financial indicators			
			Inputs			Output
			Salaries	Direct costs	Investments	Total revenues
Proposed input and output improvements (%) per inefficient unit	CCR	2016	-81.60%	-68.69%	-87.45%	0.00%
		2017	-75.41%	-72.70%	-59.77%	0.00%
		2018	-75.82%	-79.37%	-83.27%	0.00%
		2016-2018	-77.39%	-73.25%	-80.76%	0.00%
	BCC	2016	-52.37%	-61.90%	-76.91%	2.13%
		2017	-50.97%	-59.49%	-46.19%	5.60%
		2018	-45.98%	-60.13%	-63.34%	0.70%
		2016-2018	-49.83%	-60.35%	-67.31%	3.74%

Source: Authors' work based on DEA-Solver-Pro calculations.

efficiency itself does not necessarily imply the reference set membership. An example supporting this statement is DQOA in 2018 in the CCR model.

Differences between actual (empirical) and desired (projection) values allow an immediate insight into the magnitude of the contribution of each indicator to inefficiency and imply improvements in unit performance. These improvements, averaged across inefficient units and expressed as percentages, are presented for each indicator in Table 5. First of all, it is obvious that all three inputs cause inefficiency, each to a different extent. When averaged across the entire period under observation, investments are clearly a major inefficiency source according to both models. When observed on the annual basis, 2017 makes an exception where salaries and direct costs are the leading sources of inefficiency under CCR and BCC models respectively. On the other hand, total revenues have the least impact on efficiency. In fact, according to the CCR model, it causes no inefficiency at all, while according to the BCC model, its contribution to inefficiency is present, but negligible compared to the other three indicators. The apparent significantly greater impact of inputs than output on inefficiency is one of the expected consequences of the choice of model orientation. Given the relative contribution of each financial indicator to inefficiency presented in Figure 2, investments and total revenues obviously have the highest and lowest shares respectively. As shown, these shares depend on the assumption of returns to scale, i.e. the type of the model itself. However, the second hypothesis highlighting investments as a major source of inefficiency among the selected indicators has been confirmed.

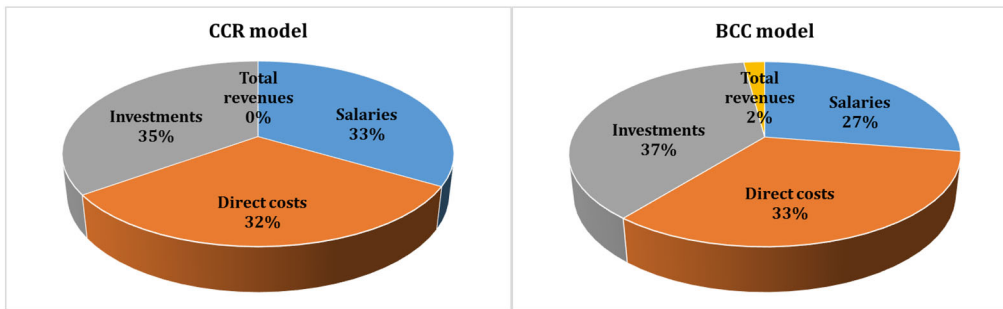


Figure 2. Input-output contribution to inefficiency based on different returns-to-scale assumptions. Source: Authors' work based on DEA-Solver-Pro calculations.

The differences among efficiency scores regarding different types of efficiency are clearly not negligible. As presented earlier, all units, with the exception of DD&NW, which operates under the most productive scale size, exhibit a certain type of inefficiency. The question that emerges is whether it is local or global. The answer should be drawn from the contributions of pure technical and scale inefficiencies to overall inefficiency. The comparison of the scores associated with different types of efficiency is given in Figure 3. Their average values, ranging from 0.4321 to 0.8077 depending on the efficiency type and the year observed, reveal that the overall inefficiency of HED units can be, to a larger extent, attributed to scale efficiency. To vividly illustrate this problem, two opposite examples have been briefly depicted. On the one hand, there is DW&WW with the scale scores notably higher than pure technical scores during the entire investigated period, indicating that, on average, the major portion of its overall inefficiency can be attributed to pure technical inefficiency, i.e. to its inefficient operations or management, rather than scale inefficiency. The examination also finds continuous increasing returns to scale (IRS), suggesting that DW&WW operates at a sub-optimal scale and therefore has a potential to improve efficiency by scaling up its activities and thus achieve an optimal scale. However, removing the pure technical inefficiency should be achieved by embracing the strategies from benchmarking units, naturally in the context of the input and output variables selected. On the other hand, there is DPEF with the full pure technical efficiency which is caused by its use of the smallest amount of inputs (for more information, see Theorem 4.3 in Cooper et al., 2006) although it is the second lowest in the technical efficiency score. Given that it is calculated as the ratio of these two efficiencies, the scale efficiency in such case is extremely low, and it could be interpreted that the global inefficiency of this unit is mainly attributed to disadvantageous conditions it operates under. Nevertheless, irrespective of the inefficiency type and extent, less than optimally required outcomes were generated with respect to the utilized resources.

DD&NW is clearly the most efficient unit. On the other hand, considering the disparity of results associated with different efficiency types, it is hard to recognize the least efficient unit. Nevertheless, DCAT is the only unit with technical, pure technical, and scale efficiency scores continuously below 0.5.

The general conclusion, based on all the numbers presented above, is that pure technical efficiency has a much milder effect on overall efficiency than scale

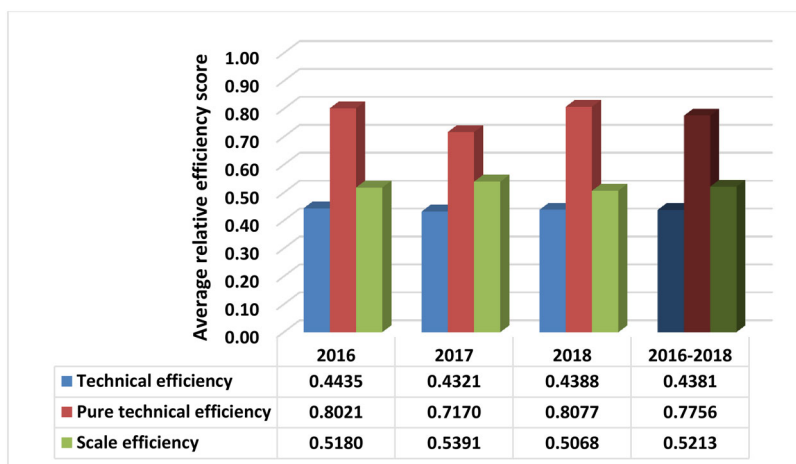


Figure 3. Decomposition of (in)efficiency in different years.

Source: Authors' work based on DEA-Solver-Pro calculations.

efficiency. Since all technically inefficient units are characterized by IRS, they need to expand their operations to reach the optimal scale. The actual feasibility of this request is primarily based on the idea of empirical relative efficiency and sustained by the underlying premise supporting the DEA method. In line with this idea, each unit is benchmarked against the other existing homogeneous units and, if inefficient, should look up to those efficient chosen to form its reference set. The empirically sustained premise is that, if a unit can generate a specific level of output employing particular input levels, other units of similar scale should be able to accomplish the same thing.

It is evident that all of the above claims require a more intense investigation of the causes behind such outcomes and the obligation to take adequate measures for upgrading units' efficiency. This particularly includes a more thorough investigation of investments as the input with the most significant contribution to inefficiency. Nevertheless, the task of finding means to achieve the improvements proposed here is not the subject of this paper, but remains the responsibility of the management of the HED under consideration.

Traditional econometric techniques for frontier models, such as stochastic frontier analysis, thick frontier analysis and distribution free analysis, have in common that they depend on a priori assumptions that are difficult to test (Wagenvoort & Schure, 1999). Similarly, there are some limitations in using DEA, such as the measurability of input and output data, the homogeneity of DMUs, the rule of thumb, etc. Although all these limitations were met in this study, it would be interesting to use one of the aforementioned parametric approaches to test the robustness of the results obtained from the DEA. However, due to space limitations, it would be too extensive to introduce an additional method and perform further analysis within this paper, but this possibility certainly remains open for future research.

5. Discussion and conclusion

Institutes of public health, as providers of preventive public health services, play a very important role in maintaining the health and sustainability of the entire health system. The significance of measuring their efficiency is consequently highly emphasized. Nevertheless, the available literature on the efficiency measurement of health-care services does not sufficiently cover empirical measurements of the efficiency of public health prevention services. The Teaching Institute of Public Health of the County of Primorje-Gorski Kotar was the basis of this study, its HED in particular, as the one that is most profitable and most market-oriented, with the main task of preserving and promoting the human health with regard to the environmental factors. Its twelve constituting units show great variability in activities, and also significant interconnectedness. Some departments generate significant revenues and, as such, stand out as bearers of “core” activities, while some of them focus more on technical support for other departments. Nevertheless, they are equally important when analyzing the efficiency of the entire observed department.

Significant difference in business performance between units has become an increasing issue for the management, so the financial performance, i.e. financial perspective investigation is necessary for consideration of the possible comparative causes of inefficiency. Two hypotheses were formulated in this context, where the first one proposed a significant between-unit variability in financial performance and the second one highlighted investments as a major source of inefficiency among the selected indicators. Therefore, the research was aimed at evaluating efficiency based on financial inputs and outputs of the HED's units for the three-year period 2016–2018 by applying a nonparametric evidence-based approach, i.e., DEA. Furthermore, three types of efficiency were calculated: technical, pure technical, and scale efficiency, in order to determine whether the cause of inefficiency is related to inefficient operation of management or disadvantageous conditions.

As evident from the presented analysis, the results revealed significant between-unit, between-year, and between-efficiency-type differences in performance ratings. From the total number of units that form the HED department, only three can be considered efficient; DD&NW throughout the entire period in both the CCR and BBC model, and DPEF and DBM&E in the BCC model. Some of these differences can be explained by different nature of services and activities provided by individual units, ranging from core activities (DQOA and DD&NW) to more technical activities (DCAT and DSES). Likewise, for example, DPEF is a relatively new department, which has been in existence for three years. These differences are less pronounced in the case of pure technical efficiency than in the cases of technical and scale efficiency, which leads to the conclusion that the overall inefficiency of HED units can be generally attributed to scale efficiency.

In the search for the modalities of organizing and delivering public health services, the above implies the need to consider the possibility of improving efficiency by scaling up their activities and expanding their operations in order to achieve an optimal scale. However, organizations can be complex, as in this example of institutes of public health, and this complexity must be considered in developing their strategies for change. The first hypothesis proposing a significant between-unit variability in

financial performance as a consequence of different units' activities has been confirmed and therefore, an organisational restructuring could be suggested upon the obtained DEA results. As the units partly need to collaborate in order to provide their service, and as some of them predominantly provide ancillary services, determination of the main functions, i.e. departments which can be characterized as the main activity bearers, is more than logical.

As stated earlier, no efficiency evaluation of services provided by public health institutes is represented in the existing empirical research, except for the research carried out by Vitezić et al. (2016). In addition to the similarities and differences between that and this study, given in the section on indicators and model specification, their results should be further compared. However, this can only be discussed in a small part related to the models matching in the selection of indicators and in the model type and orientation. At a glance, there are significant (at both unit and department level) differences in the number of efficient units and their rank, the efficiency scores and their variability, the type of units' returns to scale (increasing, constant, decreasing), the proposed input and output improvements, etc. For example, the lowest efficiency rating in this study (0.17) is approximately 3.5 times lower than in Vitezić et al. (0.60). As the latter gives neither the original values nor the descriptive statistics of the variables, it is difficult to explain the origin of such large differences. However, both studies highlight investments and direct costs as two major sources of inefficiency under the VRS assumption.

Generally, organizational units constituting the healthcare system have been faced with increasing pressure to improve efficiency. Accordingly, the research results of this study provide implications for health policy makers and managers in the first place, when considering modalities of an effective institutional form of providing public health services with an emphasis on preventive ones or those improving the performance of organizational units. The implications of the research results are aimed at further research and testing the efficiency of the entire network of public health institutes.

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References

- Acheson, D. (1988). *Public health in England: The report of the Committee of Inquiry into the future development of the public health function*. The Stationery Office.
- Adang, E. M., & Borm, G. F. (2007). Is there an association between economic performance and public satisfaction in health care? *The European Journal of Health Economics : HEPAC : Health Economics in Prevention and Care*, 8(3), 279–285. <https://doi.org/10.1007/s10198-007-0045-6>
- Adler, N., Friedman, L., & Sinuany-Stern, Z. (2002). Review of ranking methods in the data envelopment analysis context. *European Journal of Operational Research*, 140(2), 249–265. [https://doi.org/10.1016/S0377-2217\(02\)00068-1](https://doi.org/10.1016/S0377-2217(02)00068-1)
- Alonso, J. M., Clifton, J., & Díaz-Fuentes, D. (2015). The impact of New Public Management on efficiency: An analysis of Madrid's hospitals. *Health Policy (Amsterdam, Netherlands)*, 119(3), 333–340. <https://doi.org/10.1016/j.healthpol.2014.12.001>
- Andrews, L. (2018). *Integrating human health, ecology and built environment design: A TDAR Gardens Intervention case study with an informal slum community in the Peruvian Amazon* [PhD thesis]. University of Washington.
- Asandului, L., Popescu, C., & Fătuțescu, I. P. (2015). Identifying and explaining the efficiency of the public health systems in European countries. *Annals of the Alexandru Ioan Cuza University - Economics*, 62(3), 357–368. <https://doi.org/10.1515/aicue-2015-0024>
- Asandului, L., Roman, M., & Fătuțescu, P. (2014). The efficiency of healthcare systems in Europe: A data envelopment analysis approach. *Procedia Economics and Finance*, 10, 261–268. [https://doi.org/10.1016/S2212-5671\(14\)00301-3](https://doi.org/10.1016/S2212-5671(14)00301-3)
- Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, 30(9), 1078–1092. <https://doi.org/10.1287/mnsc.30.9.1078>
- Barton, H., & Tsourou, C. (2000). *Healthy urban planning*. Spon Press.
- Bulog, A. (2018). Research methods in the public and environmental health. In A. Krulec, A. Ovca, & S. Tajnikar (Eds.), *Zbornik povzetkov Slovenskih dnevnih sanitarnega inženirstva 2018 z mednarodno udeležbo* (pp. 8–9). Narodna in univerzitetna knjižnica.
- Carrillo, M., & Jorge, J. M. (2017). DEA-like efficiency ranking of regional health systems in Spain. *Social Indicators Research*, 133(3), 1133–1149. <https://doi.org/10.1007/s11205-016-1398-y>
- Centers for Disease Control and Prevention. (2014). Ten Essential Public Health Services and How They Can Include Addressing Social Determinants of Health Inequities. Retrieved July 11, 2019, from https://www.cdc.gov/publichealthgateway/publichealthservices/pdf/Ten_Essential_Services_and_SDOH.pdf
- Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2(6), 429–444. [https://doi.org/10.1016/0377-2217\(78\)90138-8](https://doi.org/10.1016/0377-2217(78)90138-8)
- Cooper, W. W., Seiford, L. M., & Tone, K. (2006). *Introduction to data envelopment analysis and its uses: with DEA-solver software and references*. Springer Science & Business Media.
- Coutts, C. (2010). Public health ecology. *Journal of Environmental Health*, 72(6), 53–55.
- De Nicola, A., Gitto, S., & Mancuso, P. (2011). A two-stage DEA model to evaluate the efficiency of the Italian health system (MPRA Paper No. 39126). University Library of Munich.
- Garavaglia, G., Lettieri, E., Agasisti, T., & Lopez, S. (2011). Efficiency and quality of care in nursing homes: An Italian case study. *Health Care Management Science*, 14(1), 22–35. <https://doi.org/10.1007/s10729-010-9139-2>
- Gattoufi, S., Oral, M., & Reisman, A. (2004). Data envelopment analysis literature: A bibliography update (1951–2001). *Journal of Socio-Economic Planning Sciences*, 38(2-3), 159–229.
- Gholami, R., Higón, D. A., & Emrouznejad, A. (2015). Hospital performance: Efficiency or quality? Can we have both with IT?. *Expert Systems with Applications*, 42(12), 5390–5400. <https://doi.org/10.1016/j.eswa.2014.12.019>

- Hollingsworth, B. (2008). The measurement of efficiency and productivity of health care delivery. *Health Economics*, 17(10), 1107–1128. <https://doi.org/10.1002/hec.1391>
- Honari, M. (1999). Health ecology: An introduction. In M. Honari, & T. Boleyn (Eds.), *Health ecology: Health, culture and human-environment interaction* (pp. 1–34). Routledge.
- Jackson, R. J., & Kochtitzky, C. (2001). Creating a healthy environment: The impact of the built environment on public health. *Sprawl Watch Clearinghouse*. Retrieved on July 23, 2019, from <http://www.sprawlwatch.org/health.pdf>
- Jennings, V., Browning, M. H. E. M., & Rigolon, A. (2019). Cultural ecosystem services meet broader frameworks in public health. In *Urban green spaces* (pp. 31–46). SpringerBriefs in Geography.
- Kaitelidou, D., Katharaki, M., Kalogeropoulou, M., Economou, C., Siskou, O., Souliotis, K., Tsavalias, K., & Liaropoulos, L. (2016). The impact of economic crisis to hospital sector and the efficiency of Greek public hospitals. *EJBSS*, 4, 111–125.
- Kattel, R., Cepilovs, A., Drechsler, W., Kalvet, T., Lember, V., & Tönurist, P. (2013). Can we measure public sector innovation? A literature review. *LIPSE Working Papers*, 2, 1–45.
- Kelava, I., Šutić, I., Pavišić, V., Salać, N., & Aleksandar, B. (2018). Health safety of water for human consumption in the city of Čabar in the period of 2012–2016. *International Journal of Sanitary Engineering Research*, 12(1), 27.
- Kohl, S., Schoenfelder, J., Fügner, A., & Brunner, J. O. (2019). The use of Data Envelopment Analysis (DEA) in healthcare with a focus on hospitals. *Health Care Management Science*, 22(2), 245–286. <https://doi.org/10.1007/s10729-018-9436-8>
- Kolda, A., Petrić, I., Mucko, M., Gottstein, S., Žutinić, P., Goreta, G., Ternjej, I., Rubinić, R., Radišić, M., & Udovič, M. G. (2019). How environment selects: Resilience and survival of microbial mat community within intermittent karst spring Krčić (Croatia). *Ecohydrology*, 12(2), e2063. <https://doi.org/10.1002/eco.2063>
- Liu, J. S., Lu, L. Y., & Lu, W. M. (2016). Research fronts in data envelopment analysis. *Omega*, 58, 33–45. <https://doi.org/10.1016/j.omega.2015.04.004>
- Liu, J. S., Lu, L. Y., Lu, W. M., & Lin, B. J. (2013). A survey of DEA applications. *Omega*, 41(5), 893–902. <https://doi.org/10.1016/j.omega.2012.11.004>
- Marić, M., Vučenović, M., Šutić, I., & Bulog, A. (2018). The organochlorine pesticides in food samples. *International Journal Sanitary Engineering Research*, 12(1), 4.
- Martini, G., Berta, P., Mullahy, J., & Vittadini, G. (2014). The effectiveness–efficiency trade-off in health care: The case of hospitals in Lombardy, Italy. *Regional Science and Urban Economics*, 49, 217–231. <https://doi.org/10.1016/j.regsciurbeco.2014.02.003>
- McGlynn, E. A. (2008). Identifying, categorizing, and evaluating health care efficiency measures. Final Report (prepared by the Southern California Evidence-based Practice Center – RAND Corporation, under Contract No. 282-00-0005-21). Agency for Healthcare Research and Quality Publication No. 08-0030.
- Mitropoulos, P., Kounetas, K., & Mitropoulos, I. (2016). Factors affecting primary health care centers’ economic and production efficiency. *Annals of Operations Research*, 247(2), 807–822. <https://doi.org/10.1007/s10479-015-2056-5>
- National Health Care Strategy 2012–2020. (2012). Government of the Republic of Croatia, Ministry of Health of the Republic of Croatia. Retrieved July 9, 2019, from <https://ec.europa.eu/migrant-integration/librarydoc/national-health-care-strategy-2012–2020>
- Nistor, C. S., Ștefănescu, C. A., & Crișan, A. R. (2017). Performance through efficiency in the public healthcare system—A DEA approach in an emergent country. *Studia Universitatis Babes-Bolyai Oeconomica*, 62(1), 31–49. <https://doi.org/10.1515/subboec-2017-0003>
- Nunamaker, T. R. (1983). Measuring routine nursing service efficiency: a comparison of cost per patient day and data envelopment analysis models. *Health Services Research*, 18(2 Pt 1), 183–208.
- Nuti, S., Daraio, C., Speroni, C., & Vainieri, M. (2011). Relationships between technical efficiency and the quality and costs of health care in Italy. *International Journal for Quality in Health Care : journal of the International Society for Quality in Health Care*, 23(3), 324–330. <https://doi.org/10.1093/intqhc/mzr005>

- Park, B. Z., Cantrell, L., Hunt, H., Farris, R. P., Schumacher, P., & Bauer, U. E. (2017). State public health actions to prevent and control diabetes, heart disease, obesity and associated risk factors, and promote school health. *Preventing Chronic Disease*, 14, E127. <https://doi.org/10.5888/pcd14.160437>
- Prüss-Ustün, A., Wolf, J., Corvalán, C., Neville, T., Bos, R., & Neira, M. (2016). Diseases due to unhealthy environments: an updated estimate of the global burden of disease attributable to environmental determinants of health. *Journal of Public Health*, 39(3), 464–475.
- Rabar, D. (2013). Evaluation of Croatia's regional hospital efficiency: An application of data envelopment analysis. In U. Bacher et al. (Eds.), *Interdisciplinary Management Research IX* (pp. 649–659). Josip Juraj Strossmayer University of Osijek & Hochschule Pforzheim University.
- Rabar, D. (2010). Ocjenjivanje efikasnosti poslovanja hrvatskih bolnica metodom analize omeđivanja podataka. *Ekonomski pregled*, 61(9-10), 511–533.
- Sarkis, J. (2007). Preparing your data for DEA. In J. Zhu & W. D. Cook (Eds.), *Modeling data irregularities and structural complexities in data envelopment analysis* (pp. 305–320). Springer.
- Sherman, H. D. (1984). Hospital efficiency measurement and evaluation. Empirical test of a new technique. *Medical Care*, 22(10), 922–938. <https://doi.org/10.1097/00005650-198410000-00005>
- Stefko, R., Gavurova, B., & Kocisova, K. (2018). Healthcare efficiency assessment using DEA analysis in the Slovak Republic. *Health Economics Review*, 8(1), 6. <https://doi.org/10.1186/s13561-018-0191-9>
- Steingraber, S., & Hill, K. (2002). Human health and design: An essay in two parts. In K. Hill, & B. Johnson (Eds.), *Ecology and design: Frameworks for learning* (pp. 191–214). Island Press.
- Strategic Plan of the Ministry of Health for 2020-2022. (2019). Retrieved July 10, 2019, from <https://zdravlje.gov.hr/UserDocsImages/2018%20Financijski%20planovi,%20strate%C5%A1ki%20dokumenti%20i%20javna%20nabava/Strate%C5%A1ki%20plan%20MZ%202020.-2022.-za%20objavu.pdf>
- Tsekouras, K., Papathanassopoulos, F., Kounetas, K., & Pappous, G. (2010). Does the adoption of new technology boost productive efficiency in the public sector? The case of ICUs system. *International Journal of Production Economics*, 128(1), 427–433. <https://doi.org/10.1016/j.ijpe.2010.07.041>
- Vitezić, N., Šegota, A., & Setnikar-Cankar, S. (2016). Measuring the efficiency of public health services by DEA. *International Public Administration Review*, 14(4), 27–48.
- Wagenvoort, R., & Schure, P. (1999). The recursive thick frontier approach to estimating efficiency (No. 1999/02). Economic and Financial Report.
- Winslow, C. E. (1920). The untilled fields of public health. *Science (New York, N.Y.)*, 51(1306), 23–33. <https://doi.org/10.1126/science.51.1306.23>