# Comparison of the effectiveness of health systems in the European countries- two-stage DEA model

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## Abstract

This article compares the efficiency of health systems in selected European countries using two-stage data envelopment analysis (DEA), based on data from the EUROSTAT database. In the first step, DEA efficiency scores were calculated for health care systems and, subsequently, the external variables describing lifestyle were used to calculate the truncated regression.

Health care resources (physicians, nurses, hospital beds, financial outlays, life expectancy in health) included in the health care system and the lifestyle factors of the population are: alcohol consumption, smoking, overweight. The root cause of health systems inefficiencies is health behaviours. The main practical significance of this study is that the conclusions drawn from the results can help policy makers to evaluate the performance of health systems as well as contribute to the identification of directions for improvement in the future.

**Key words: health system, lifestyle factors, efficiency, two-stage data envelopment analysis**.

## Introduction

Costs in health care systems have been trending upward for many years and have forced governments and policy makers to take an interest in the productivity, efficiency, and inefficiency of health care. Inefficient use of health care resources continues to be a major reason for increased spending on health care services. As a result, health care reforms are being implemented to eliminate inefficiencies and reduce costs. One of the main goals of health reforms is to maximize the well-being of treated patients, improve the quality of care provided and, as a result, stem the trend of rising costs.

There are many factors that influence health outcomes. In addition to the quantitative indicators by which health outcomes can be measured in a way, other factors that influence people's health, such as lifestyle, health behaviours, social environment, and genetic factors, are also important. The Robert Wood Johnson Foundation emphasises that "health is more than health care" (RWJF 2019) and thus health system analysis cannot be limited to determining the technical efficiency of the use of the resources involved, such as medical personnel, health care infrastructure, or financial resources. This set of resources should be expanded to include non-medical factors affecting population health (OECD 2010; Rettenmaier and Wang 2013; RWJF 2019;). Woolf and Aron (2013) emphasise that in order to fully reflect the complexity of the health system, it is necessary to consider the links between public health(population-based services) and medical care (provided to individual patients). In their view, both components should be taken into account during international comparisons of health systems.

There have been many comparative studies of health systems in different groups of countries around the world, conducted mostly with the use of the non-parametric method of data envelopment analysis (DEA). From the perspective of the DEA models, two main approaches can be distinguished (Ozcan and Khushalani 2017; Mitropoulos 2019). The traditional approach treats the units (called Decision Making Units – DMUs) being evaluated (health systems) as a black box, assuming that the production process is a function of initial inputs and final outputs without information about the activities performed within each DMU (e.g. Retzlaff-Roberts et al. 2004; González et al. 2010; Hadad et al. 2013; Mitropoulos 2019). To overcome these problems, an approach using the Data Envelopment Analysis (DEA) model and regression analysis is often used (Afonso and Aubyn 2011; de Cos and Moral-Benito 2014).

In order to determine the effectiveness of a complex health system, it is not enough to simply compare the effectiveness of the health care systems of selected countries. Other factors that influence population health or perceptions of health, such as environmental factors related to public health, should also be included in analyses. This goal can be achieved by using the two-stage Data Envelopment Analysis (two-stage DEA) model.

The results of such analyses can give rise to system improvements using best practices (Mitropoulos 2019; Papanicolas and Smith 2013). Health expenditure is one of the main areas of public expenditure (Mitropoulos 2019), thus the increase in the efficiency of publicly funded health systems should also provide better access to services for the public. In European Union (EU) countries, health care expenditures grew faster than national income, which is largely the result of population ageing and medical innovation, as well as the observed inefficiency of health care systems. They also emphasise that health outcomes are influenced by past and present lifestyle behaviours and environmental factors beyond the immediate control of the health care system.

The purpose of this study is to assess the relative technical efficiency of the health systems of European countries. To achieve the goal of the article, the analysis was enhanced by a second stage in which DEA scores are regressed on several potential lifestyle variables with the use of Simar and Wilson's bootstrap procedure (2007), in order to ensure statistical proficiency.

The main practical significance of this study is that the conclusions drawn from the results can help policy makers to evaluate the performance of health systems as well as contribute to the identification of directions for improvement in the future.

The structure of this article is organised in the following way. The section "Factors affecting the efficiency of health systems" presents the relevance of the impact of non-medical factors on health systems. The section "Methodology" provides background information on the non-parametric DEA method in the context of benchmarking, the DEA-SBM algorithm used in the article, and the assumptions of truncated regression. The "Data" section presents the structure of the variables and their interrelationships, as well as basic descriptive statistics for each variable. The "Results" section presents the basic results in a concise form and their implications are discussed ("Discussion"). In the next section, "Conclusions", the possible applications of the results obtained are indicated.

## Factors affecting the efficiency of health systems

Research on health systems usually focuses on determining the impact of medical expenditures and infrastructure on population health, but the much greater importance of non-medical factors: biological, socioeconomic, and lifestyle factors affecting human health should not be overlooked (González et al. 2010; OECD 2010; Hollingsworth 2012; Rettenmaier and Wang 2013; RWJF 2019). Biological factors are gender and age structure, especially the proportion of people over the age of 65. The category of socioeconomic factors includes education level, income level, unemployment level, economic, social and cultural status of the population, as well as environmental pollution resulting from the urbanisation of the region of residence. Lifestyle factors such as smoking, alcohol consumption, dietary habits leading to overweight and obesity, as well as lack of physical activity are important contributors to increased risk of morbidity and mortality (Cawley and Ruhm 2012; Di Cesare et al. 2013; Foster et al. 2018). According to WHO (2019), smoking is one of the biggest threats to public health, killing more than 8 million people each year, of which approximately 1.2 million are the result of exposure of non-smokers to secondhand smoke.

Many health care outcomes do not result directly from system interventions but are influenced by the non-medical factors identified above (Retzlaff-Roberts et al. 2004; OECD 2010; Papanicolas and Cylus 2017). A similar view is presented by Spinks and Hollingsworth (2009) who stated that commonly used indicators of health outcomes related to life expectancy mainly reflect population lifestyle, socioeconomic and environmental factors. Unhealthy lifestyles are associated with a higher risk of mortality, while the positive impact of healthy lifestyles on life expectancy may increase the average age of the population, which in turn may contribute to higher burdens on health care systems, affecting their efficiency (European Union 2015).

Non-medical factors affecting health have been variously addressed in previous studies. Retzlaff-Roberts et al. (2004) included health care variables: hospital beds, Magnetic Resonance Imagers (MRI), physicians, expenditure on health percentage of GDP. On the other hand, the environmental variables used included school expectancy, GINI and percentage of male and female use smoking. These environmental variables are treated as exogenously fixed inputs because, according to the authors, they are beyond the short-term discretionary control of policy makers. They used a DEA model with non-discretionary inputs, which results in the variables remaining unchanged in the efficiency calculations. Infant mortality and life expectancy were used as outputs. Another common way to account for non-medical inputs is to perform a two-step analysis (e.g. Afonso and Aubyn 2011; Hadad et al. 2013; de Cos and Moral-Benito 2014), which uses two different sets of variables. The set of variables underlying the health production function is used to estimate efficiency indices using the DEA method. In the second step, the influence of non-medical factors, which are in a way shaped and controlled by policy makers and influence the functioning of health production processes, is considered by regressing efficiency scores on non-medical factors.

Afonso and Aubyn (2011) used the DEA/TOBIT two-step procedure in their article. Three outputs were used to determine the efficiency of health care systems in OECD countries: life expectancy, infant survival rate and potential years of life (not lost). In contrast, the following were used as inputs to the DEA model: number of practicing physicians, nurses, acute care beds and MRI. While in the second stage, the following were used to estimate the Tobit regression model: GDP per capita, educational level, percentage of obesity, and tobacco consumption.

Hadad et al. (2013) used baseline variables representing health care resources, plus GDP per capita and consumption of fruit and vegetables, in the DEA models. The estimated efficiency scores were used as dependent variables in a linear regression. The following were used as independent variables: fat intake, GINI index, unemployment, public expenditure share, environmental health score, and 0-1 variables representing different aspects of health care organisation, such as gatekeeping, number of insurers, disease management programmes, etc. An extended version of this method of calculating the efficiency of health systems is presented by de Cos and Moral-Benito (2014). In addition to the efficiency index calculated on the basis of the DEA model with typical resource variables, the efficiency index for the SFA model and the WHO index were also calculated (WHO 2000). The efficiency indices determined on this basis served as dependent variables in the regression model. Twenty indices indicating institutional health care solutions were used as independent variables.

Using the network DEA model, Ozcan and Khushalani (2017) represent a different view on the treatment of lifestyle factors, stating that they are, admittedly, beyond the control of medical care systems but are regulated and controlled by government institutions responsible for the public health in each country. This is reflected in legislation and health education activities regarding, among other things, the harmfulness of smoking, alcohol consumption and obesity. According to network DEA assumptions, two sets of variables related to environmental variables and medical care are evaluated simultaneously.

## Methodology

As health gains importance on the global agenda, there are growing needs to accurately measure its complex dimensions and assess the impact of health policy changes. A good understanding of how health systems work enables appropriate policy-making as well as the best possible use of the resources available. This can only be achieved if there is a firm foundation of metrics and evaluation (Hollingsworth 2012).

Hollingsworth (2012) suggests that efforts should be made to make health system efficiency measurement more useful to recipients. Such analyses are required to have valid and robust results, which can be achieved by taking into account appropriate methodological requirements, including adequate model specification, incorporation of sensitivity analysis and data testing in the model building process, and appropriate interpretation of results that takes into account the importance of all key issues related to health systems performance. This opinion is supported by Wendt (2014), who indicates that comparative studies best assess the efficiency of similar health care systems in different countries. The above requirements are met by the DEA method, which has a vast array of variants, provided that an appropriate model is selected and the basic assumptions that DMUs are engaged in similar activities, produce comparable products or services (thus enabling the definition of a common set of outputs) using a similar range of resources, and operate in comparable environments are met (Dyson et al. 2001; Avkiran 2011). According to Cook et al. (2014), in selecting a model, several key issues should be considered, such as the purpose of the study; the DMUs being compared; the inputs and outputs characterising the DMUs; the returns to scale; the relationship between the number of DMUs being compared and the summed number of inputs and outputs; as well as the orientation of the model.

In its original version (Charnes et al. 1978), DEA was seen as a representation of a production process in which the required resources are inputs and the products are outputs. In this case, the DEA model maps the processing of inputs into outputs and the outcome is the production frontier created by efficient DMUs. Despite the strong association of DEA with the theory of production in economics, as the method has evolved, it has also found applications to benchmarking. When applying DEA to benchmarking, the characteristics that describe DMUs do not represent resources and products, in standard manufacturing terms. The benchmarking literature uses terms such as indicators or metrics. The problem arises of how to classify these performance measures of units into input and output categories for use in DEA (Cook et al. 2014). When DEA is used for benchmarking, it is assumed that inputs are measures of less-the-better performance and outputs are measures of more-the-better performance(Afonso and Aubyn 2011; Hadad et al. 2013; Cook et al. 2014; Ouenniche et al. 2014; Tone 2017).

Another issue in formulating a DEA model is the presence of economies or diseconomies of scale. A DMU may be too small to function at optimal efficiency or too large, making it difficult to manage. If a variable returns to scale (VRS) model is used, where there are no inherent scale effects, small and large DMUs will tend to overestimate efficiency scores. The VRS model can only be used if the returns to scale can be unambiguously proven (Dyson et al. 2001). Ozcan and Khushalani (2017) find that the VRS model requires an a priori assumption about whether the health systems examined have increasing or decreasing returns to scale. Such assumptions cannot be made due to the unavailability of literature. Studies comparing different countries often use indicator variables, relating the values of the studied factors to scaling variables such as GDP, population, or number of employees (Dosi et al. 2006; González et al. 2010;), so the CRS model with constant returns to scale is justified.

Depending on whether inputs or outputs are controllable, the model is assumed to be input- or output-oriented, respectively (Thanassoulis 2001). This enables the evaluation of the inefficiency of either inputs or outputs. It is also possible to use a non-oriented model. An example of this is the study by Ozcan and Khushalani (2017), where a non-oriented NDEA CRS model was used. Such a model enables the assessment of input excesses and output shortfalls directly.

In accordance with the previous description of the DEA method, a Slack-Based Measure (SBM) output-oriented model with fixed scale effects was adopted. This is appropriate in this context because health systems aim to maximise health benefits rather than keep them constant (Hadad et al. 2013).

Let a set of DMUs consist of $\mathrm{J} = \{1,2,..., n\}$ facilities, each of which has *m* expenses and *s* outcomes. Output-oriented SBM efficiency of $\rho_o^*$ for $\mathrm{DMU}_\mathrm{o} = (\mathbf{x}_o, \mathbf{y}_o)$ is defined as (Tone 2011):

$$\frac{1}{\rho_o^*} = \max_{\lambda, s^-, s^+} 1 + \frac{1}{s}\sum_{r=1}^{s} \frac{s_r^+}{y_{ro}} \tag{1}$$

with the following conditions:

$$\begin{aligned} & x_{io} = \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- \quad (i = 1,..., m) \\ & y_{ro} = \sum_{j=1}^{n} y_{rj}\lambda_j + s_r^+ \quad (r = 1,..., s) \\ & \lambda_j \geq 0(\forall j) \quad s_j^- \geq 0(\forall i) \quad s_r^+ \geq 0(\forall r) \\ & \sum_{j=1}^{n} \lambda_j = 1 \end{aligned} \tag{2}$$

To rank SBM-efficient units, the Super-SBM model can be used. Assuming that $\mathrm{DMU}_\mathrm{o} = (\mathbf{x}_o, \mathbf{y}_o)$ is SBM-efficient, i.e. it meets the $\rho_{IO}^* = 1, \quad \mathbf{s}^- = \mathbf{0}, \quad \mathbf{s}^{+*} = \mathbf{0}$ conditions, super efficiency can be defined for $(\mathbf{x}_o, \mathbf{y}_o)$, as the optimal objective function of the $\rho^*$ value, according to the following formula (Tone 2011):

$$\rho_O^* = \min_{\bar{\mathbf{x}}, \bar{\mathbf{y}}, \boldsymbol{\lambda}} \frac{1}{(1/s)\sum_{r=1}^{s}(\bar{y}_r / y_{ro})} \tag{3}$$

with the following conditions:

$$\begin{aligned} & \bar{x}_i \geq \sum_{j=1, j \neq o}^{n} x_{ij}\lambda_j \quad (i = 1,..., m) \\ & \bar{y}_r \leq \sum_{j=1, j \neq o}^{n} y_{rj}\lambda_j \quad (r = 1,..., s) \\ & \bar{\mathbf{x}} \geq \mathbf{x}_o \quad \bar{\mathbf{y}} \leq \mathbf{y}_o \quad \bar{\mathbf{y}} \geq \mathbf{0} \quad \boldsymbol{\lambda} \geq \mathbf{0} \\ & \sum_{j=1}^{n} \lambda_j = 1 \end{aligned} \tag{4}$$

In the second stage, the (previously calculated) DEA SBM efficiency scores will be used as the dependent variable ( $\hat{\rho}_0^{\ *}$ ), regressing them on potential exogenous (environmental) variables (zi):

$$\hat{\rho}_i^* = \alpha + z_i\beta + \xi_i \tag{5}$$

where $\xi_i$ is a statistical noise with distribution limited by $\xi_i \geq 1 - \alpha - z_i\beta$ because DEA efficiency scores are greater than or equal to unity

Some problems arise from the fact that the actual DEA efficiency scores are not observed but estimated and may be serially correlated in unknown ways. Furthermore, the error components $\xi_i$ are correlated with $z_i$ because the input and output variables are correlated with environmental variables. To obtain unbiased results for β estimates, Simar and Wilson's (2007) bootstrap procedure was applied using bootstrapped truncated regression. The STATA program was used to estimate the regression model.

## Data

The data used in this paper were sourced primarily from the 2016 Eurostat database. The study covered 30 countries, i.e. all EU28 countries, as well as Iceland and Norway. The selected year offered the most complete data set. The inputs used for the DEA SBM model included primary health care resources, taking into account the medical personnel, medical infrastructure, and expenditure. These variables are as follows: PHYS – number of physicians per hundred thousand inhabitants; NUR_MID – number of nurses and midwives per hundred thousand inhabitants; BEDS – number of hospital beds per hundred thousand inhabitants; EXP_TOT_GDP – total health care expenditures as a percentage of the gross domestic product (GDP). The outputs included the expected number of healthy life years at 65, separately for men (HLE_65_M) and women (HLE_65_F), which is elaborated upon later in this section. The selection of variables was based on the analysis conducted in the introduction. The adoption of an age limit of 65 for outputs was motivated by the fact that this age group has significantly higher medical care needs than younger people.
Alcohol consumption, smoking, and overweight were included as independent variables for the truncated regression model. These variables included ALC – the average number of litres of pure alcohol per capita per year; CURR_SMOKER – the proportion of people declaring themselves as current smokers; OVERWEIGHT – the proportion of overweight people in the population. The variables were selected based on the analysis contained in the "Factors affecting the efficiency of health systems" section. Table 1 shows descriptive statistics for all variables.

Table 1 Descriptive statistics of the variables included in the analyses

| Variable | Role | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| PHYS | Input | 355.3 | 65.0 | 241.6 | 513.0 |
| NUR_MID | | 923.6 | 377.0 | 350.0 | 1,804.9 |
| BEDS | | 486.5 | 168.6 | 233.9 | 806.3 |
| EXP_TOT_GDP | | 8.5 | 1.7 | 5.0 | 11.5 |
| HLE_65_F | Output | 9.5 | 3.2 | 4.2 | 16.6 |
| HLE_65_M | | 9.4 | 3.0 | 4.4 | 15.5 |
| ALC | Independent variable | 11.2 | 2.0 | 6.7 | 15.4 |
| CURR_SMOKER | | 24.8 | 4.5 | 16.7 | 34.8 |
| OVERWEIGHT | | 51.6 | 3.9 | 43.8 | 59.6 |

Source: own calculations based on data from Eurostat 2016.

There is significant cross-country variation in the set of variables describing health care performance. For the values of inputs representing human resources and infrastructure, the ratio of maximum to minimum value is as follows: PHYS 2.1; NUR_MID 5.2; BEDS 3.4. Health expenditure is a vital factor, averaging 8.5% of GDP, nonetheless, it amounts to only 4.4% in Latvia while reaching as high as 15.5% in Iceland. Two variables, HLE_65_F and HLE_65_M, were adopted for the outputs due to the significant cross-country differences between men and women compared to the life expectancy at birth (LE), which is frequently used in health care system studies, and which is longer for women in all EU countries by an average of 5.9 years (for 2016), with a minimum value of 3.2 years in the Netherlands and a maximum value of 10.2 years in Lithuania. The HLE_65 value is 0.0-1.5 years higher for women in half of the countries studied and 0.2-1.5 years higher for men in the other half. In such a case, adopting values without a gender breakdown is not justified.

The used lifestyle factors also show significant cross-country variation. One in four people in the countries surveyed is currently a smoker and the average annual alcohol consumption per person is 11 litres. The variation for smokers ranges from 16.7% in Sweden to 34.8% in Bulgaria. For alcohol drinkers, it is from 6.7 litres in Italy to 15.4 litres in Lithuania. This shows that both habits and the effectiveness of prevention policies in this area vary. The problem of overweight is much worse. On average, one in two residents is overweight, with this characteristic having a similar value across all countries studied (from 43.8% in Italy to 59.6% in Malta). This may lead one to conclude that the obesity epidemic is not country-dependent.

## Results

The health system efficiency scores, calculated based on the DEA-SBM model with fixed scale effects described by equation (3), are presented in the columns labelled "Score" in Table 2. Complementing the efficiency score values are the rankings in the "Rank" column, which are determined by the results of the superefficiency model described by equation (3). The column labelled "Peers" shows how many times it occurs in the case of fully efficient countries to enable its use as a benchmark for inefficient countries. Calculations were performed using the MaxDEA Ultra 6.19 software.

Table 2 Efficiency scores for European countries

| Country | | Score | Rank | Peers | Country | | Score | Rank | Peers |
|---|---|---|---|---|---|---|---|---|---|
| Austria | AT | 0.517 | 26 | | Italy | IT | 0.935 | 11 | |
| Belgium | BE | 0.878 | 12 | | Latvia | LV | 0.482 | 28 | |
| Bulgaria | BG | 1.000 | 7 | 0 | Lithuania | LT | 0.502 | 27 | |
| Croatia | HR | 0.477 | 29 | | Luxembourg | LU | 0.765 | 16 | |
| Cyprus | CY | 1.000 | 2 | 10 | Malta | MT | 1.000 | 10 | 0 |
| Czech Republic | CZ | 0.725 | 19 | | Netherlands | NL | 0.751 | 17 | |
| Denmark | DK | 0.799 | 15 | | Norway | NO | 0.841 | 13 | |
| Estonia | EE | 0.581 | 25 | | Poland | PL | 1.000 | 9 | 5 |
| Finland | FI | 0.672 | 22 | | Portugal | PT | 0.666 | 23 | |
| France | FR | 0.825 | 14 | | Romania | RO | 0.684 | 21 | |
| Germany | DE | 0.746 | 18 | | Slovakia | SK | 0.438 | 30 | |
| Greece | EL | 1.000 | 3 | 0 | Slovenia | SI | 0.711 | 20 | |
| Hungary | HU | 0.624 | 24 | | Spain | ES | 1.000 | 6 | 1 |
| Iceland | IS | 1.000 | 4 | 6 | Sweden | SE | 1.000 | 1 | 12 |
| Ireland | IE | 1.000 | 5 | 9 | United Kingdom | UK | 1.000 | 8 | 7 |
| | Mean | 0.787 | | SD | 0.189 | | Min | 0.438 | |

Source: own calculations.

Full health care system efficiency was attained by 10 countries (SE, CY, EL, IS, IE, ES, BG, UK, PL, MT). The average efficiency was 78.7%, with a cross-country variation of 18.9 percentage points. Among the fully efficient countries, 3 are "efficient by default" – they do not represent a benchmark for any inefficient country since they have unique characteristics that allow them to be at the efficiency frontier. Slovakia had the lowest health care system efficiency, with three countries achieving efficiencies below 50%.

For the further computational procedure, the efficiency scores were calculated as 1/score. Table 3 shows the estimated health care system inefficiency scores. The calculations were performed according to the procedure described by Simar and Wilson (2007).

Table 3. The determinants of inefficiency scores

| | Bias-adjusted coefficients | 95% bootstrap confidence intervals | |
|---|---|---|---|
| | | low | up |
| ALC | .0429 | -.0145* | .1038 |
| Current_smo_t | .0594*** | .0343 | .0868 |
| Overweight | .0374 | .0064 | .0694 |

* Value of zero does not fall within 80% confidence interval

Source: own calculations.

In the first column, bias-adjusted coefficients of a basic regression model have been indicated. The second column is a presentation of the lower and upper bounds of the 95% bootstrap confidence interval. Therefore, this has been used in order to prove the statistical significance of the estimated coefficients. It is worth noted, that the statistical significance presents that the value of zero does not decline within the certainty interval linked with a coefficient under particular research.

When recalling result of DEA formulation from equition 5, a positive signal of the estimated regression parameter presents that, ceteris paribus, an escalation in a variable corresponds to higher inefficiency (lower efficiency), whereas a negative sign of estimated parameter proves lower inefficiency (greater efficiency) (Wolszczak-Derlacz and Parteka 2011).

Lifestyle factors such as smoking, alcohol use and being overweight contribute to health care system inefficiency. The estimation results reveal that the coefficient associated with ALC – the average number of litres of alcohol per capita – is not statistically significant at the 5% level. Only from the 38% level does this variable significantly affect health care system inefficiency. The inclusion of another variable related to alcohol consumption – the percentage of the population reporting drinking alcohol each week – produced a very similar result (it too was statistically insignificant at the 5% significance level). The Overweight variable indicating the percentage of people who are overweight is significant at a level of about 10%. Additionally, smoking affects health care system inefficiency at every level of significance.

## Discussion

Since A. Charnes, W. Cooper and E. Rhodes (Charnes et al. 1978) introduced the DEA method, more than ten thousand articles have been published on both theoretical advances and applications of DEA in a wide variety of industries.

Research on the effectiveness of health care systems using the basic CCR and BCC models is very popular. However, the two-stage DEA is rarely used to study the effectiveness of health systems. Research regarding the effectiveness of hospitals (De Nicola et al. 2013), or primary health care (Marschall, Flessa 2011) in one country can be found more often (Gearhart, Michieka 2018), than comparing health systems in different countries.

The effectiveness of health care systems calculated in this study, with the use of the SBM model, averaged almost 79% in all the 30 countries studied and presents the moderate level. If, however, the studied countries are divided into two groups, i.e. the countries of Western Europe (including Cyprus and Malta) and the countries of Eastern Europe, the differences in the level of effectiveness are significant. The average efficiency for the countries of Western Europe was 86.3% and for the countries of Central and Eastern Europe it was 65.7%, hence the difference in average amounts to 20.6 pp.

According to the second step (level), mainly lifestyle factors such as smoking, alcohol consumption, overweight, GP level or education level were used in econometric models. The factors used in the truncated regression model, such as smoking and being overweight, significantly exacerbate the ineffectiveness of health systems. To a smaller extent, it is alcohol consumption.

While the relationship between smoking and the risk of developing specific medical conditions is well understood, relatively little is known about the risks of alcohol and BMI. This requires further epidemiological research and more extensive simulation modeling. These factors are not the only ones that have an impact on the effectiveness of health systems.

Hadad et al. (2013) showed the significance of environmental factors (sanitary ones) for health care system efficiency; their analysis led to conclude that the average fat intake in countries that have achieved 100% health care system efficiency is lower than in countries which health care systems remain inefficient. The impact of the fruit and vegetable consumption variable was found to be insignificant. Afonso and Aubyn (2011) models did not include a variable related to alcohol consumption. However, variables related to smoking and obesity were used. Both showed a positive interaction with health care system inefficiency. Previous research confirms the direction of efficiency variation.
The analysis of the functioning of health systems is difficult to be performed due to the lack of a single health outcome indicator due to the immaterial nature of services provided by the health care sector and the differences in the goals of health care systems implemented by decision-makers in different countries. There is also no standardization in terms of lifestyle in the country and the variables used are only proxies.

To increase health care system efficiency (improve output), population lifestyle, diet, routine and habit changes, as well as differences concerning the environmental variables, should be introduced first.

## Conclusion

The study aimed to assess the efficiency of the health systems of 30 European countries and identify the factors shaping it. A two-stage analysis combining both parametric and nonparametric methods was proposed. First, the technical efficiency of 30 European countries was measured using non-parametric frontier methods. The second stage of the analysis involved combining the technical efficiency ratings of individual health care systems with characteristics describing the lifestyles of populations of the specific countries. Unlike many other studies, bootstrapped truncated regression was used to ensure the accuracy of the estimates.

Health care system improvement efforts are necessary because they play a key role in every country, effectively influencing the public's perceived safety level, as well as the wider quality of life. The fact that health care expenditures are among the primary public spending areas is also a significant factor. The complexity of these systems makes it difficult to define them precisely, which means that there is no uniform model for analysing them.

Population health outcomes do not depend solely on the health care system efficiency – i.e. the level of resource employment, such as the number of hospitals, physicians and other medical infrastructure. The population's past and present lifestyle behaviours and environmental factors are also crucial. Population ageing is also a major burden on the health care system. Thus, health systems analyses are multidimensional, requiring the use of appropriate methods. The average health care system efficiency is at a relatively high level of 79%. Nonetheless, as evidenced by today's crisis, countries with low health care resources fare worse in emergencies.

Further research should proceed towards finding other determinants influencing the effectiveness of health care systems, such as the level of education, income and related inequalities, consumption of fruit and vegetables, the state of the natural environment, etc.

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