Innovation, lifestyle, policy and socioeconomic factors:

An analysis of European quality of life

Abstract

The need to innovate in order to adapt to continuous changes in the environment affects all production units, but this may be particularly true of the health sector, which is key to ensuring healthy lives. However, the day-to-day running of a country absorbs nearly all its economic resources, with health innovation being consistently overlooked and only coming to the fore in isolated cases of public emergencies. This research has a twofold objective. First, it analyses the efficiency of national expenditure on research and development (R&D) in the health sector and the changes in productivity that occurred in the period 2009-2017, using DEA-Bootstrap and the Global Malmquist Index. Second, regression models are used to quantify the relative importance of said efficiency for the health status of the population, introducing other aspects that a priori could also be expected to affect this status. The sample is composed of 23 European OECD countries, and a biennial data analysis is carried out to ensure the results are stable over time, as well as to study the particular case of each of the countries analysed. The results reveal that efficiency is not determined by the volume of resources allocated to health innovation. The budget that Norway assigns to R&D in the health sector is only a quarter that of Germany's, but it more efficiently transforms that spending into quality of life. In addition, the level of happiness, the country's wealth, and spending on health are the factors that have the greatest effect on the perceived health status of the European population.

Keywords: Health Innovation, DEA-Bootstrap, Global Malmquist Index, Perceived health status.

1. Introduction

The aim of a healthcare system is to improve the quality of life of the population, reducing suffering and preventing mortality where possible. Faced with the unquestionable magnitude of the task of managing this system, developed countries have allocated a budget of between 8 and 10% of national Gross Domestic Product (GDP) to the health sector in the last 10 years, according to the Organisation for Economic Co-operation and Development (OECD) statistics. However, this amount is sometimes not enough to cope with the continuous changes in the environment in which the sector performs its functions. The ageing of the population, the emergence of new chronic diseases, new trends in health markets, along with changes in the organization of healthcare workers, are some of the elements driving the need to allocate greater economic resources (Akca et al., 2017). This is a sector undergoing a process of constant adaptation to new technologies, where efficiency ensures social welfare (Asandului et al., 2014).

In this environment, innovation plays a crucial role, driving the conversion of knowledge and research into more effective practices that help identify solutions to new scenarios, improving the quality of care and the delivery of health services (Côté-Boileau et al., 2019). Healthcare systems typically adapt, innovate and improve fairly slowly, but at a pace that is appropriate for the new developments emerging (Naylor et al., 2015; Velthoven et al., 2019). The introduction of these developments disrupts the system and requires changes in the way professionals act and in funding, as well as in the regulations and policies that affect system performance (Christensen et al., 2015; Baker and Denis, 2011; Christensen and Overdorf, 2000). Moreover, the complexity, dynamism and diversity in healthcare systems mean that innovation is approached in a way that is not consistent over time or space (Alvehus et al., 2016).

All this makes it difficult to assess the efficiency not just of healthcare systems, but also of innovation processes, where the population's level of well-being, socioeconomic stability and health status, among other factors, have a major influence on productivity (Asandului et al., 2014). In more developed countries, the population demands assurance of high quality health services, leading to longer life expectancy. However, in such a rapidly-shifting environment, the efficiency of the healthcare system is far from being a homogeneous, stable feature. The continual emergence of new diseases requires attention and the allocation of additional human and economic resources.

Production systems need to adapt to new circumstances and introduce innovative products and processes to ensure they retain their position in the market: the health sector is no exception. Innovation in medical and health sciences channels economic and human resources into research on such fundamental issues as human behaviour, medical treatment and the proliferation of diseases. The results do not always materialize into intangible assets such as patents and trademarks; in many cases, innovation translates into greater longevity and a healthier life for the population. Nevertheless, despite its huge importance, there is still not enough spending on health research and development (R&D) to meet global healthcare demands. According to the World Health Organization (WHO), in terms of budget items in 2020, the Western Pacific region tops the list with 0.07% of its GDP, while in European countries this percentage drops to 0.03%. At any rate, these amounts are too small when faced with the new diseases afflicting humankind.

This research seeks to cover one of the less-studied aspects in this field: R&D as a vehicle for ensuring the population enjoy a healthy life. Specifically, this paper has a twofold objective. First, to quantitatively assess medical innovation in order to determine the correct use of public and private funds allocated for this purpose. Using an extension of Data Envelopment Analysis (DEA)—namely, a DEA-Bootstrap approach—the aim is to evaluate the efficiency of innovation expenditure in the medical and health sciences sector by the authorities and universities of 23 European countries belonging to the OECD, during the period 2009-2017. In addition, the changes in the productivity of R&D expenditure during this period will be analysed to determine their source; in other words, whether these changes are due to an improvement in efficiency or to technological change. To that end, the Global Malmquist Index (GMI) will be used. Second, the empirical analysis carried out seeks to clarify which factors determine the health status of the population; to that end, three pooled regression models will be estimated, also assessing the efficiency of innovation in this sector. Achieving these two objectives will enable an assessment of the differences between the countries analysed, identifying possible patterns of behaviour that can facilitate the adoption of measures aimed at fostering and improving their citizens' quality of life, which is the ultimate goal of medical and health sciences.

Health organizations must tackle continual challenges in order to improve the population's quality of life. Doing so requires the introduction of new practices and services that complement the diligent efforts of healthcare workers. Innovation in healthcare systems is a key factor enabling countries' proper development, ensuring a healthy life for their citizens (Janssen and Moors, 2013; Thune and Mina, 2016). By providing quantitative data on the outcomes achieved by individual countries, it will be possible to assess the proper use of public and private funds and to detect unanticipated deviations that will require corrective measures to prevent potential disruptions. Silva et al. (2018) demonstrate that innovation boosts the ability to meet collective needs, in addition to addressing health inequalities and providing an appropriate response to the current challenges facing healthcare systems.

The literature contains numerous studies focused on the analysis of the efficiency of hospitals (Büchner et al., 2016; Chowdhury and Zelenyuk, 2016; Kohl et al., 2019), national expenditure on health (Cetin and Bahce, 2016; Top et al., 2020), as well as others centring on the knowledge and development of innovation processes aimed at specific empirical cases such as glaucoma (Consoli and Ramlogan, 2011) or rheumatological disease (Essen and Lindblad, 2013), among others. However, this paper presents a novel approach in that it focuses on quantifying the efficiency of the R&D expenditure needed to ensure the proper functioning of national healthcare systems, which must constantly adapt to a changing environment and take on the challenge of improving quality of life.

The research carried out represents a contribution to the existing literature for several reasons: (1) it provides a wide-ranging comparison of the efficiency of 23 European nations' expenditure on R&D in health over nine years; (2) it applies DEA-Bootstrap, enabling an analysis of efficiency over time by means of a single production frontier, and making it possible to establish a ranking of the countries according to their level of efficiency; (3) the period under analysis includes an economic crisis involving major cuts to healthcare in many of the countries in the sample, and so the GMI reveals whether, despite these circumstances, countries have been able to properly channel their resources into raising life expectancy; (4) the results of the GMI also facilitate an understanding of the composition of the changes in productivity, identifying their source; (5) and lastly, this study provides evidence on which factors influence the health status of the population, thus helping to guide authorities' policies on R&D expenditure in the health sector.

2. Literature review

In recent decades, innovation has been seen as a critical factor for the development and survival of countries' healthcare systems (Lansisalmi et al., 2006; Janssen and Moors, 2013; Thune and Mina, 2016; Cleven et al. 2016). However, while it is more readily undertaken and financed in chemical and medical engineering—because the results translate into new drugs or technologies that improve treatments—analyses of innovation in healthcare systems as drivers of improvements in people's quality of life have only recently started to emerge. Some studies have focused on specific technologies (Galbrun and Kijima, 2009, 2010; Consoli et al., 2016), others on hospitals as innovative organizations (Ugurluoglu et al., 2013; Yang, 2014; Dias and Escoval, 2015), on professionals (García-Goni et al., 2007; Xu and Kesselheim, 2014) and even on patient care (Oftedal et al., 2019).

R&D can be defined in different ways depending on how it is conceptualized. In this research we use the definition provided by the Frascati Manual (OECD, 2015), which states that "Research and experimental development (R&D) comprise creative work undertaken on a systematic basis in order to increase the stock of knowledge, including knowledge of man, culture and society, and the use of this stock of knowledge to devise new applications. It covers three activities: basic research, applied research and experimental development". Studies analysing the efficiency of innovation enable an assessment of the scope of the output achieved with the inputs used. In the health field, these empirical analyses are strongly conditioned by the complexity of the analysed sector and the limitations of the related statistical information (Frogner et al., 2015). The literature includes research aimed at measuring efficiency in this sector, using individual performance indicators and composite indices, the results of which have sometimes been used to compare different healthcare systems and rank them according to their performance (Tandon et al., 2000; Tchouaket et al, 2012; Goncharuk, 2017). However, there are fewer studies focusing on analysing the efficiency of national R&D expenditure in the health sector.

Studies by Wang et al. (1999) and the WHO (2000) sparked an initial interest in determining the efficiency of healthcare around the world. They were followed by others that formed the basis for the development of a new body of literature on this subject (Jamison et al., 2001; Salomon et al., 2001; Evans et al., 2001; Hollingsworth and Wildman, 2003). However, it was soon noted that the choice of variables substantially affects the results; according to Jacobs et al. (2006), given the characteristics of the sector, the analyses have to be oriented towards evaluating healthcare outcomes.

Based on the identification of a production function, the DEA method can be used to evaluate the productivity of a Decision-Making Unit (DMU) by comparing its relative technical efficiency with that of the rest of the sample. The choice of inputs/outputs that characterize the DMUs is conditioned by the objectives of the research. Table 1 presents papers that estimate the efficiency of healthcare in various countries. It shows the possible combinations of variables used, as well as the different methodologies applied. In the past decade there has been a proliferation of this type of research on the efficiency of national healthcare systems, whereas previous studies primarily focused on determining the efficiency of hospitals (Hollingsworth, 2008). Only a few studies analyse aspects related to political factors as determinants of efficiency (Bhat, 2005; Wranik, 2012; Hadad et al., 2013; Lee and Kim, 2018). In terms of innovation, Ancarani et al. (2016) investigate how the acquisition of technology affects the efficiency of different hospital wards, moderated by variables relating to the management and context of the centres.

Table 1. Review of the literature on efficiency in healthcare systems

Health innovation is playing an ever more prominent role in areas such as digital health, the application of robotics to healthcare, regenerative medicine, biosensors and 4D mapping (European Commission, 2017). In this regard, Mihai et al. (2020) have shown that digital innovation is an important determinant of health status. However, this is not the only perspective; there is a wide variety of actors in healthcare systems (professionals, patients, researchers, suppliers, etc.) whose knowledge must be efficiently coordinated in order to improve levels of care, and to facilitate the development, dissemination and use of innovation aimed at benefiting health service users (Malerba, 2002). Kim et al. (2016) carry out a review of the state-of-the-art in healthcare quality, with particular reference to technological and management innovation. Recently, Proksch et al. (2019) have focused their research on analysing the possible relationship between the existence of strong national innovation systems and health innovation systems. Rivard and Lehoux (2020) have compiled the ideas of professionals who design, develop and commercialize health innovations, revealing the need to ensure stakeholder responsibility.

Nevertheless, to this day, innovation and healthcare remains a major challenge for researchers, with studies unable to capture the perspective of those responsible for setting health policy or the limited decision-making power of users of these services. In the most developed countries, healthcare systems need comprehensive reform and reorganization to adapt to the challenges of the future and to be able to offer sustainable and innovative health services and products (Cobelli, 2020). All this has motivated the focus of the empirical analysis carried out in this research, examining some of the less-studied aspects of healthcare systems, with innovation efficiency as the central element.

3. Methodology

Given the twofold aim of this research, the empirical analysis is divided into two stages involving the application of different methodologies and variables. In the first stage, technical efficiency is calculated using an extension of DEA, and the GMI to estimate the possible changes in productivity that occurred during the study period. The use of DEA-Bootstrap is proposed as a way of overcoming the limitations of DEA, which mainly stem from the sensitivity of the results to sampling variability, to the quality of the data and to the presence of outliers (Herrera and Pang, 2005; Lee et al., 2020). Then, in the second stage, the determinants of health status are estimated by means of pooled Ordinary Least Squares (OLS) regression. The efficiency calculated in the first stage is used, together with other variables that enable the analysis of markedly different aspects of the dependent variable, namely: (1) lifestyle of the population, (2) socioeconomic characteristics of each country, and (3) public resources. The literature confirms that these factors are determinants of the health status of the population (Retzlaff-Roberts et al., 2004; Medeiros and Schwierz, 2015).

Restrictions in terms of the availability of statistical information on all the variables meant the sample had to be reduced to 23 European countries, with a biennial analysis carried out for the period 2009-2017. The time horizon analysed helps ensure that the conclusions drawn are stable over time, preventing specific issues from distorting the results.

Variables

The essential focus of this research is on innovation in medicine, where the benefits of advances measured in terms of improvements in quality of life, rather than in patents, emerge over the long term; for this reason, the empirical analysis has been carried out every two years, making it possible to deal with gaps in the statistical information[1]. The first stage of the analysis estimates the efficiency of health innovation, with the composition of the inputs/outputs that define the production function being determined by the research objective (Table 2). The literature on innovation supports the correct choice of inputs used; R&D expenditure is the key variable in this type of analysis because

[1] Due to missing information, it was occasionally necessary to supplement the database with data from the following year.

it encompasses both staff costs and R&D-related costs (Han et al., 2016; Wang et al., 2016; Min et al., 2020).

Table 2. Definition and source of variables included in the DEA-Bootstrap and GMI

The robustness of the outputs used to reflect the quality of the healthcare system is likewise supported by a broad literature on efficiency (Retzlaff-Roberts et al., 2004; United Nations Statistics Division, 2011; Hadad et al., 2013; Medeiros and Schwierz, 2015; Storto and Goncharuk, 2017). As the proposed DEA-Bootstrap model is output-oriented, meaning the aim is to maximize outputs using the available resources, the IMR has to be converted into infant survival rate (ISR = (1000-IMR) / IMR). ISR can be interpreted as the number of surviving infants as a proportion of the total that died during the first year of their life; higher values can be attributed to a better healthcare system (Lee and Kim, 2018). Table 3 shows, for the 23 European countries under study, the main descriptive statistics of the inputs/outputs and their correlations.

Table 3. Descriptive statistics and correlations for inputs/outputs

In the second stage of the study, the determinants of the health status of the European population are analysed. To that end, the variables are divided into three groups according to clearly differentiated areas that could guide health policies: lifestyle, socioeconomic environment, and public policy (Table 4). In addition, the efficiency calculated using DEA-Bootstrap is introduced to evaluate its importance relative to the other aspects evaluated.

Table 4. Definition and source of the variables included in regression models

The dependent variable in all the regressions is perceived health status (HS). Published by the OECD, this value represents the percentage of the population aged 15 and over who consider their health to be good/very good or even excellent. Table 5 shows the descriptive statistics and correlations of the variables that represent the analysed factors. No multicollinearity problems are detected in the regressions, none of the variables are found to be excessively correlated and the Variance Inflation Factor (VIF) for each of the explanatory variables is below 2.

Table 5. Descriptive statistics and correlations for regression variables

All the variables used in the regression are log-transformed in order to smooth the variability, make the data more homogenous and help ensure the robustness of the estimates.

Models: DEA-Bootstrap, Global Malmquist Index, pooled OLS regression

In the economic literature, technical efficiency has primarily been measured through two approaches, DEA and stochastic frontier analysis. While the former uses linear programming to determine the production frontier that establishes the maximum level of efficiency, the latter applies econometric techniques. Both have proved suitable in a wide variety of fields related to economics and management (Fried et al., 2002; Zhang et al., 2003; Franco and Leoncini, 2013; Titko et al., 2014; Loukil, 2016). However, when dealing with scenarios involving multiple inputs/outputs and in the presence of non-linearity, DEA has been shown to be superior (Hoff, 2007; Guan and Chen, 2010a). Banker and Natarajan (2008) corroborate this conclusion regarding the advantage over parametric methods when estimating the efficiency of individual DMUs.

DEA is a non-parametric technique initially introduced by Farrell (1957). There is extensive literature that supports its use as a precision tool for calculating the technical efficiency of a DMU compared to others in the same group. It is based on the theory of production, where the definition of a production function establishes a mathematical relationship between inputs and outputs, solved by linear programming models. The score of efficiency calculated is measured as each DMU's distance from the production frontier, which is made up of those DMUs that are fully efficient.

Following on from Farrell's pioneering work, the paper by Charnes, Cooper and Rhodes (1978) enabled the development of DEA under the assumption of Constant Returns to

Scale (CRS), where increases in outputs correspond to identical increases in inputs. In response to this limitation, Banker, Charnes and Cooper (1984) introduced DEA under Variable Returns to Scale (VRS); this approach not only allowed for a different ratio of variation between inputs and outputs, but also facilitated the distinction between technical efficiency, scale efficiency and pure technical efficiency. In addition, another factor that could condition the level of efficiency registered by DMUs is whether the model is input or output oriented.

Given the research objective of the present study and the variables selected, the output-oriented model has been chosen, whereby the aim is to maximize the outputs using the available resources. Moreover, the assumption of VRS has been applied as it enables greater accuracy by eliminating the limitations of CRS. In addition, an intertemporal analysis is considered appropriate to help ensure the stability of the estimates and to facilitate the comparison between countries over the period analysed (Mittal et al., 2005; Cruz-Cázares et al., 2013).

The use of the DEA-Bootstrap model in similar environments is supported by extensive literature on this subject (Ni Luasa et al., 2018; See and Yen, 2018; Kim and Kim, 2019). The scores obtained provide bias correction and stochastic estimates, minimizing data contamination by statistical noise (Simar and Wilson, 2000). The resampling process has been repeated 2000 times, facilitating approximations of the sampling distribution of the original estimates. The difference between efficiency calculated with standard DEA and DEA-Bootstrap is the bias corrected by this procedure. Countries that achieve a level of efficiency equal to one are at the frontier; that is, they have been completely efficient in transforming inputs into outputs[2].

The Malmquist index introduced by Caves et al. (1982) explains the change in total factor productivity caused by changes in efficiency and/or technology. However, it suffers from two problems, which have been solved by the GMI: (1) it does not satisfy the property of circularity, whereby the change in productivity in one period may be explained as the product of changes in productivity in preceding subperiods; and (2) there is the possibility of infeasibilities in the calculation of the distance functions across periods (Pastor and Lovell, 2005; Oh, 2010; Wang et al., 2012). The GMI results are consistent with those obtained through the intertemporal DEA-Bootstrap, underlining the robustness of the

[2] Shephard's distances are employed in the model, taking the reciprocal value (1/value)

analysis carried out. If the score obtained is higher than one, the productivity has increased in the time horizon analysed. Conversely, a score equal to or lower than one indicates that it has remained unchanged or even decreased, respectively. The changes that have occurred may be due to (1) Technical Efficiency Changes (TEC), caused by better use of the available technology and/or changes in scale, and (2) Technological Changes (TC) as a result of progress.

Finally, three pooled OLS regression models have been estimated for the sample of 23 countries over 5 years; the Breusch-Pagan test confirms that this treatment is preferable to panel data estimation (Roodman, 2009; Labra and Torrecillas, 2014).

Model 1 $$HS_{it} = \beta_0 + \beta_1 EFF_{it} + \beta_2 AC_{it} + \beta_3 FC_{it} + \beta_4 E_{it} + \beta_5 HLS_{it} + \mu_{it} \quad (1)$$

$$i = 1, 2, 3, \dots, 23 \; countries \qquad t = 2009, 2011, \dots, 2017$$

where,

HS: perceived health status

EFF: efficiency obtained through DEA-Bootstrap

AC: alcohol consumption

FC: fruit consumption

E: education

HLS: happiness / life satisfaction

μ: random perturbation

In this model, the variables representing the aspects of the population's lifestyle that could affect HS are analysed together with EFF. A priori, all of them except AC are expected to be significant and have a positive coefficient. In small doses alcohol is not harmful but excessive consumption alters quality of life.

Model 2 $$HS_{it} = \beta_0 + \beta_1 EFF_{it} + \beta_2 GDP_{it} + \beta_3 MA_{it} + \beta_4 WL_{it} + \mu_{it} \quad (2)$$

$$i = 1, 2, 3, \dots, 23 \; countries \qquad t = 2009, 2011, \dots, 2017$$

where,

HS: perceived health status

EFF: efficiency obtained through DEA-Bootstrap

GDP: Gross Domestic Product per capita

MA: median age of population

WL: working life

μ: random perturbation

Model 2 incorporates socioeconomic aspects that, together with EFF, can have a direct effect on the quality of life of a society. In the proposed specification, EFF and GDP are expected to positively affect HS ($\beta_1>0$; $\beta_2>0$), while an ageing population is expected to have a negative impact ($\beta_3<0$). Regarding the coefficient corresponding to WL, its expected sign is more ambiguous because a longer working life positively affects the wealth of the population, and by extension, HS. However, the opposite could also be argued: a longer working life may be harmful to health and have negative effects on citizens' quality of life.

Model 3 $$HS_{it} = \beta_0 + \beta_1 EFF_{it} + \beta_2 HE_{it} + \beta_3 EE_{it} + \mu_{it} \qquad (3)$$

$$i = 1, 2, 3, \dots, 23\ countries \qquad t = 2009, 2011, \dots, 2017$$

where,

HS: perceived health status

EFF: efficiency obtained through DEA-Bootstrap

HE: health expenditure

EE: environmental expenditure

μ: random perturbation

Lastly, Model 3 analyses, together with EFF ($\beta_1>0$), two public policies that a priori are expected to have a positive effect on HS ($\beta_2>0$; $\beta_3>0$). As authorities increase their budgets allocated to addressing health needs and environmental protection, the population's quality of life should improve.

4. Results and Discussion

In the first stage of the analysis, a production function was estimated to determine the efficiency of European countries' biennial innovation expenditure. These countries are OECD members, characterized by similar economic and social standards. It can therefore be assumed that the sample meets the conditions of homogeneity required for DEA.

The objective of the empirical analysis is not to appraise the volume of resources allocated to R&D in the area of health. Rather, the aim is to assess which country has been best able to transform this expenditure into an improved quality of life for its population, measured in terms of healthy lives and infant survival rates. The first columns of Table 6 show the results of the DEA-Bootstrap as the mean efficiency obtained for each country in the period 2009-2017 (EFF mean), as well as its standard deviation (EFF SD) and the number of times a country has been fully efficient (Nº EFF = 1).

The results reveal that Norway is the country that has most efficiently used its resources in health innovation; its mean value for EFF is close to 1 (0.975), a result that has not registered substantial variations over the analysed period (EFF SD = 0.009), and in two years it achieved maximum efficiency. Two countries that registered potentially surprising results are Greece and Germany. In the years under study, Greece was severely hit by the economic crisis that began in 2008 and has experienced swingeing budget cuts in all areas of the economy. However, regardless of the monetary amount, the results show that it would only have to increase output by 7% to reach full efficiency. Germany on the other hand, a country characterized by its consistently sound economic development, and the European country that allocates the most resources in this regard, is not able to properly channel these funds: it could achieve improvements of 15% if it used all its resources appropriately.

Slovakia, Latvia, Estonia and Slovenia are the bottom-ranked countries. These Eastern European nations have a very small budget for innovation in health services, but much higher than that of Iceland. However, the latter is able to make much better use of its resources in order to improve the quality of life of its population; it would only have to increase its outputs by 10%, a level of improvement far lower than the other countries, where the equivalent figure exceeds 20%.

Table 6. Efficiency scores of the intertemporal DEA-Bootstrap and Global Malmquist Index (2009-2017)

The GMI determines the growth in factor productivity as a result of changes in efficiency (TEC) and/or the technology used (TC). On average, the sample analysed appears fairly stable (mean GMI = 0.961) and, at a disaggregated level, it can be observed that greater technological progress is a driver of efficiency in European health services (mean TC = 1.030). In addition, the results reveal a lack of correspondence between efficiency levels and changes in productivity. In the period 2009-2017, only Spain, the United Kingdom and Finland recorded increases in productivity, and not all of these countries are among the top-ranked nations. For example, Finland, which would have to achieve a 20% increase in its outputs with the resources used (mean EFF = 0.805), is the leading country in terms of productivity growth (GMI=1.0987), a result which can mainly be attributed to changes in technical efficiency (TEC = 1.089).

A very different situation is that of Norway, which, despite leading the efficiency ranking, is shown by the GMI to have experienced a decline of nearly 5% (GMI= 0.947) due to changes in technical efficiency (TEC= 0.865). This has been offset to a degree by technological improvements of nearly 10% (TC=1.096). A similar situation is that of Belgium, albeit with more extreme values. Even though this country allocates more economic resources to R&D in the health sector than Norway, it has more room for improvement in its management (mean EFF = 0.906) while in terms of productivity it has experienced a decline of 7% (GMI= 0.930). However, during the analysed period it has made substantial technological improvements of over 100% (TC = 2.036).

The literature has shown that the health status of a population is the product of a combination of three basic aspects: public resources, lifestyle and socioeconomic factors (Joumard et al., 2008). Following this line of research and in order to provide more precise knowledge, the second stage of this research involves estimating three intertemporal models through pooled OLS regression, in order to individually analyse these different factors that could influence the health status of the population, together with the efficiency levels obtained by the DEA-Bootstrap[3]. Table 7 shows the results of these models; the R-

[3] The Breusch-Pagan test confirms the absence of heteroscedasticity, therefore indicating that it is appropriate to run a pooled OLS regression.

squared measures of goodness of fit for all three show that between 72% and 66% of the variance is explained. The coefficients have been standardized, enabling a comparative analysis of the variables to assess the relevance of each one, but no comparisons can be made between models.

Table 7. Standardized coefficients for the estimation of health status

The efficiency of R&D expenditure is significant in the three models analysed, and thus positively affects the health status of the population. Furthermore, it can be seen that overall the signs are in line with a priori expectations. The excessive consumption of alcohol and the ageing of the population adversely affect the quality of life of the population.

Performing an individual analysis by models, in the first model, which analyses the impact of the population's lifestyle in each of the countries in the sample, it is found that happiness is the factor that has the greatest influence on health status. Alcohol consumption, fruit consumption, and the efficiency of R&D spending in the health sector all register a very similar weight (-0.224, 0.232 and 0.293, respectively), whereas educational level is in last place (0.120), but is still significant. Regarding socioeconomic factors (Model 2), it is the wealth of the country measured in real GDP per capita that has the greatest effect on quality of life (0.665), followed by innovation efficiency (0.217) and population ageing (-0.180). Finally, in terms of public measures (Model 3), countries' spending on healthcare needs has a standardized beta of 0.626. In addition, the importance of efficiency in innovation (0.298) should not be disregarded, nor the public resources dedicated to protecting the environment (0.118), both factors that improve social welfare and therefore health status.

The empirical analyses carried out make it possible to address the proposed objectives of this research, yielding national-level quantitative data on the correct use of public and private funds aimed at improving quality of healthcare systems. In addition, it has been shown that the level of efficiency in innovation and certain socioeconomic factors have a major influence on the health status of the population. These results add to the existing literature analysing the health status of the population measured by the mortality ratio (Berger and Messer, 2002) or life expectancy and infant mortality (Or et al., 2005; Afonso and St Aubyn, 2006; Nixon and Ullman, 2006). However, each study should be analysed individually; the results are not comparable even if the same variables were used. The level of efficiency achieved by each country/region is estimated on the basis of similarity with the rest of the observations in the sample, relating to a certain production function. That said, the conclusions and recommendations could be extrapolated to other economies in which the initial conditions are similar (Brown, 2006). Furthermore, no other articles to date have included the efficiency of innovation and public policies as possible determinants of quality of life.

Conclusions

The research carried out seeks to determine the level of efficiency of R&D expenditure on medical and health services in 23 OECD countries over a nine-year period, using DEA-Bootstrap and the GMI. In addition, the analysis quantifies the relative importance of the different aspects that a priori could be expected to affect the health status of the population, using diverse variables that capture lifestyle, socioeconomic level and the public resources allocated for this purpose.

The European countries analysed are highly developed, albeit with certain specific management characteristics which are reflected in the efficiency scores. On average, the results of the DEA-Bootstrap show that with the monetary amount dedicated to R&D in the health sector, it would be possible to increase the quality of life of the population by 14% and thereby achieve maximum efficiency, with the latter measured in terms of healthy lives and infant survival rates. Furthermore, there is no correlation between the volume of resources dedicated to R&D and the scores obtained, as reflected in the results for Greece, Iceland and Germany.

It should be borne in mind that productivity growth is conditioned by the specific economic features of the countries during the period under analysis, and has been affected by significant cuts in almost all of their budget lines. Only three countries have experienced productivity growth close to or even above 5%, as is the case of Finland. However, even taking into account these restrictions, research and innovation centres have overall been able to introduce technological advances, with related improvements quantified at 3%. Particularly notable in this regard are Denmark and Belgium, which register values for technological change of 41% and 100%, respectively.

On the other hand, the results reveal that lifestyle, socioeconomic factors, and public resources, together with efficiency in health innovation, are influential factors that should be promoted to improve the health status of the population. People's happiness/life satisfaction, the economic development of their countries, and the resources allocated to health are the parameters that have the strongest influence.

At the disaggregated level it has been shown that, to ensure a healthy life, individuals should improve their eating habits (measured in terms of fruit consumption) and educational level, and they should avoid excessive alcohol consumption. This would help soften the negative impact of the possible increase in the average age of the population, brought about by medical advances that make it possible to prolong the lifespan (median age) of people in society.

Finally, special mention should be made of public policies aimed not only at increasing and improving the management of R&D resources, but also at addressing health needs and environmental protection, issues that may be overlooked by the authorities in some countries. Nevertheless, all these policies play a major role in pandemics, where advances in medical technology are essential to combat the effects of the situation. Moreover, recent literature has raised the question of the role played by climate change as a possible driver and accelerator of the transmission of these negative effects.

This research is limited by the availability of the—sometimes incomplete—statistical data, which prevents a broader set of countries from being covered; the inclusion of more countries would provide a more comprehensive picture of the situation. Nor is it possible to analyse medical innovation measured in terms of patents, given the lack of data on inputs allocated exclusively to this purpose. The logical continuation of this research would be to broaden the spectrum of the sample by analysing other geographical areas in order to identify possible differences that could provide economic policy makers with more information. It would even be useful to perform a regional analysis to establish more precise patterns of behaviour within a country, although it would require extensive fieldwork to gather the statistical information needed to carry out such a study.

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Table 1. Review of the literature on efficiency in healthcare systems

Author(s)	Sample	Objective	Methodology	Inputs	Outputs
Hadad et al. (2013)	31 OECD countries	Compare the efficiency of different countries' healthcare systems	DEA, Super-efficiency, Cross-efficiency	Physician density In-patient bed density Health expenditure GDP per capita Consumption of fruit and vegetables	Life expectancy Infant mortality
Varabyova and Schreyögg (2013)	30 OECD countries	Comparison of the technical efficiency of the hospital sector using unbalanced panel data	DEA-Bootstrap, Stochastic Frontier Analysis	Number of beds Hospital employment Physicians Nurses	Discharges Mortality rate
Kim et al. (2016)	30 OECD countries	Productivity changes in the healthcare systems	Bootstrapped Malmquist	Health expenditure School life expectancy	Life expectancy at birth Infant mortality rate
Lam et al. (2017)	12 healthcare companies in Malaysia	Evaluate the relative efficiency of healthcare sector companies	DEA, Linear programming model	Debt to assets ratio Debt to equity ratio	Return on assets Return on equity
Storto and Goncharuk (2017)	32 European countries	Performance measurement of European healthcare systems	DEA-Slack Based Model	Medical doctors Nurses, midwives, healthcare assistants Available beds in hospitals	Ratio of infant mortality Healthy life years Life expectancy Population
Lee and Kim (2018)	35 OECD countries	Association between the efficiency of the healthcare system and policy factors	DEA-Bootstrap	Expenditure on health Practicing physicians Number of beds	Infant survival Life expectancy
Abolghasem et al. (2019)	120 countries	Propose a new methodology comprising DEA and data science	Cross-efficiency, Cluster	Population Specialist surgical Birth rate Total fertility rate Hospital beds Nurses, midwives and physicians	Mortality
Ibrahim et al. (2019)	Sub-Saharan Africa	Estimate the efficiency of healthcare systems in Sub-Saharan Africa based on health focused millennium development goals	DEA, Malmquist Productivity Index	Health expenditure Immunisation measles Immunized DPT Immunized HepB3	Life expectancy Infant mortality rate Tuberculosis rate Newly infected HIV Malaria cases reported Maternal mortality rate
Top et al. (2020)	36 African countries	Measure the healthcare system efficiency	DEA, Tobit	Health expenditure Physicians Nurses Beds Unemployment rate Gini coefficient	Life expectancy at birth 1/infant mortality rate
Kim et al (2020)	34 Asian countries	Evaluate the healthcare investment efficiency and health competitiveness efficiency of 34 developing countries in Asia	Two-stage dynamic DEA	Health expenditure Healthcare providers	Incidence of tuberculosis Mortality rate Life expectancy at birth

Table 2. Definition and source of variables included in the DEA-Bootstrap and GMI

Variable	Role	Definition	Source
Gross domestic expenditure on R&D by higher education (GERD higher education)	Input	Total intramural expenditure on R&D in medical and health sciences by universities (US Dollars, Millions, 2015).	OECD
Gross domestic expenditure on R&D by government (GERD government)	Input	Total intramural expenditure on R&D in medical and health sciences by the government (US Dollars, Millions, 2015).	OECD
Healthy life years in absolute value at birth (HL)	Output	Measures the number of remaining years that a person of a specific age is expected to live without any severe or moderate health problems.	Eurostat
Infant mortality rate (IMR)	Output	Ratio of the number of deaths of children under one year of age during the year to the number of live births in that year (per 1000 live births)	Eurostat

Table 3. Descriptive statistics and correlations for inputs/outputs

Variable		Statistics				Correlations			
		Mean	SD	Min	Max	1	2	3	4
1. GERD higher education	Input	687.14	1059.14	0.33	4953.02	1			
2. GERD government	Input	248.04	395.67	0.02	1705.89	0.76	1		
3. HL	Output	61.29	4.55	51.40	70.90	0.15	0.23	1	
4. ISR	Output	321.90	117.70	130.60	1110.10	-0.13	-0.06	0.29	1

Table 4. Definition and source of the variables included in regression models

Lifestyle		
Variable	**Definition**	**Source**
Alcohol consumption	Annual consumption of pure alcohol in litres, per person, aged 15 years old and over	OECD
Fruit consumption	Average fruit consumption per person, measured in kilograms per year.	Our World in Data
Education	Population by educational attainment levels 3-8 (%)	Eurostat
Happiness and Life Satisfaction	Share of people who say they are 'very satisfied' or 'fairly satisfied' with their life (%).	Our World in Data
Socioeconomics factors		
Variable	**Definition**	**Source**
Real GDP per capita	GDP measures the value of total final output of goods and services produced by an economy within a certain period, measured in euros per capita.	Eurostat
Median age of population	Median age of population	Eurostat
Working life	Duration of working life, measured in years.	Eurostat
Public policy		
Variable	**Definition**	**Source**
Health expenditure	Health spending per capita, constant price, measured in euros.	OECD
Environmental expenditure	Public expenditure on environmental protection, % GDP	Eurostat

Table 5. Descriptive statistics and correlations for regression variables

	Variable	Statistics				Correlations										
		Mean	**SD**	**Min**	**Max**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
1	Health status	65.93	10.71	42.60	83.20	1										
2	EFF	0.86	0.06	0.73	0.98	0.60	1.00									
3	Alcohol	10.06	1.84	6.00	14.70	-0.53	-0.39	1.00								
4	Fruit	95.82	37.28	39.39	202.17	0.47	0.34	-0.29	1.00							
5	Happiness	6.48	0.85	4.67	7.79	0.70	0.31	-0.27	0.31	1.00						
6	Education	73.53	11.39	30.80	88.00	-0.18	-0.30	0.35	-0.43	0.03	1.00					
7	GDP	28,859	17,846	8,710	82,550	0.64	0.46	-0.25	0.47	0.73	-0.13	1.00				
8	Median age	40.78	2.49	33.60	45.90	-0.35	-0.29	0.08	-0.06	-0.22	-0.04	-0.23	1.00			
9	Working life	35.68	3.45	28.80	47.00	0.29	0.10	-0.27	0.09	0.59	-0.04	0.32	-0.24	1.00		
10	Medical Exp	3,038	1,208	1,061	5,621	0.71	0.44	-0.25	0.48	0.84	-0.15	0.87	-0.07	0.42	1.00	
11	Environ Exp	0.78	0.34	-0.20	1.70	0.29	0.27	-0.21	0.26	-0.05	-0.18	0.08	-0.01	-0.24	0.10	1
	VIF						1.34	1.30	1.53	1.32	1.39	1.61	1.15	1.30	1.25	1.08

Table 6. Efficiency scores of the intertemporal DEA-Bootstrap and Global Malmquist Index (2009-2017)

	DEA-Bootstrap			Global Malmquist Index		
	EFF mean	**EFF SD**	**No EFF =1**	**GMI**	**TC**	**TEC**
Norway	0.975	0.009	2	0.947	1.096	0.865
Ireland	0.950	0.018	0	0.990	1.087	0.910
Greece	0.930	0.014	0	0.888	0.897	0.991
Spain	0.908	0.032	0	1.047	0.745	1.406
Belgium	0.906	0.005	0	0.930	2.036	0.457
Iceland	0.902	0.014	3	0.896	0.896	1.000
United Kingdom	0.898	0.015	0	1.056	1.082	0.976
Luxembourg	0.888	0.040	0	0.948	0.689	1.375
Czechia	0.886	0.009	0	0.998	0.946	1.056
Italy	0.881	0.022	0	0.972	0.885	1.098
Poland	0.867	0.005	0	0.977	0.947	1.031
Germany	0.854	0.059	0	0.972	1.090	0.892
Denmark	0.854	0.017	0	0.883	1.410	0.626
Hungary	0.839	0.016	0	0.853	0.928	0.919
Netherlands	0.838	0.012	0	0.960	1.258	0.763
Portugal	0.836	0.033	0	0.996	1.002	0.994
Lithuania	0.827	0.014	0	0.982	1.119	0.877
Austria	0.821	0.018	0	0.952	0.981	0.970
Finland	0.805	0.010	0	1.098	1.008	1.089
Slovenia	0.799	0.038	0	0.987	0.935	1.056
Estonia	0.786	0.010	0	0.922	0.754	1.223
Latvia	0.769	0.062	1	0.943	0.943	1.000
Slovakia	0.766	0.021	0	0.903	0.948	0.953
Mean	**0.860**	**0.021**		**0.961**	**1.030**	**0.979**

Table 7. Standardized coefficients for the estimation of health status

	Model 1	**Model 2**	**Model 3**
EFF	0.293***	0.217**	0.265***
Alcohol	-0.224***		
Fruit	0.232***		
Education	0.120*		
Happiness	0.464***		
GDP		0.665***	
Median age		-0.180**	
Working life		-0.089	
Medical expenditure			0.626***
Environment expenditure			0.118*
R-squared	0.72	0.67	0.66
Breusch-Pagan. Chi2 (p-value)	9.027 (0.108)	3.568 (0.467)	6.715 (0.0815)
Observations	115	115	115

Dependent variable: Health status
*** p-value < 0.01, ** p-value < 0.05, *p-value < 0.1