Research

Hacettepe Journal of Health Administration, 2018; 21(4): 641-653

The Impact of Technical Change on Healthcare Production and Efficiency

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ABSTRACT

This article measures the technical efficiency of healthcare production and estimates the impact of technical change on healthcare across OECD countries between 2000 and 2011, based on a 34 country panel data set, extending the study by Fare et al. (1997). The study adopted a DEA (Data Envelopment Analysis) based output-oriented efficiency measure to obtain the productive efficiency of each country for all given years, and used the Malmquist Index to determine the productivity growth and decompose the technical change from efficiency changes over the years. It is found that the production frontier shifted up around 0.8% annually between 2000 and 2011, with a cumulative 8.5% technical and 7.2% productivity increase over the period. Technological progress seems to be stable over time, while most of the fluctuations in productivity growth come from changes in efficiency due to utilization of new technologies.

Keywords: *Healthcare systems, Efficiency, DEA, Technical Change, Productivity Growth, OECD*

Teknik Değişimin Sağlık Üretimi ve Etkinliği Üzerindeki Etkisi

ÖZ

Bu makale, 2000 - 2011 yılları arasında, OECD ülkeleri çapında 34 ülkenin panel veri seti kullanılarak sağlık üretiminin teknik etkinliğini ölçmekte, teknik değişimin sağlık sistemleri üzerindeki etkisini hesap etmekte ve Fare ve diğerleri (1997)'nin çalışmasına devam niteliği taşımaktadır. Belirlenmiş bütün yıllara göre her bir ülkenin üretim etkinliğini elde etmek için, çıktı-tabanlı DEA (Veri Zarflama Analizi) etkinlik ölçüsü benimsenmiş, verimlilik artışını bulmak ve yıllara göre etkinlik artışlarını teknik değişimlerden arındırabilmek için de Malmquist Indeksini kullanılmıştır. Bulgular, 2000-2011 yılları arasında, üretim hadlerinin yıllık ortalama yaklaşık % 0,8 ve toplamda da, teknik açıdan %8,5, üretim verimliliğinin de %7,2 arttığını göstermektedir. Teknolojik ilerlemenin uzun vadede istikrarlı olduğu görülmekle beraber, dalgalanmalarının büyük oranda, yeni teknolojilerin kullanımı dolayısıyla verimlilik değişimlerinden kaynaklandığı görülmektedir.

Anahtar Kelimeler: *Sağlık Sistemleri, Etkinlik, VZA, Teknik Değişim, Verimlilik Artışı, OECD*

I. INTRODUCTION

Technological advances in healthcare, notably hospital care, have been dramatic over the last four decades (Färe 1997), but they have often been blamed for mounting costs of hospital care, especially in the United States. Various analysts Aaron (1991), Newhouse (1993), and Schwartz and Mendelson (1994), have argued that technological change generates the underlying growth in expenditures.

On the other hand, many studies in the literature identify technical change as the main source of healthcare improvements. Färe et al. (1994), for example, find widespread and rapid productivity growth for a sample of OECD countries from 1974 to 1989, especially for

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Submission Date: 01.05.2018; Accepted: 23.05.2018

Denmark and the USA. Likewise, Moscone et al. (2013) find a significant relationship between scientific research and the growth in healthcare productivity.

Increasing inefficiency in the hospital industry is also causing real expenditure growth as illustrated by a World Bank Paper (Wang et al. 1999) and a WHO study (WHO 2000) which made the early attempts to measure global healthcare efficiency using different performance indicators, showing enormous variance in health outcomes, despite similar income and education levels. This generated considerable interest in the measurement of healthcare efficiency.

A healthcare provider (e.g., hospital, physician, healthcare system) is efficient if it maximizes output for a given bundle of inputs or minimizes inputs used to produce a given output. The measured inputs and outputs are assumed to be homogeneous across units. We can talk about technological progress if the production frontier has shifted up over time, meaning the same input bundle can now produce more due to technological progress.

Although the initial Farrell analysis (Farrell 1957) is static, changes in efficiency can be measured over time, i.e. the frontier may shift due to technological advances. Productivity is defined as the ratio of an index of output to an index of input usage. Change of this measure over time is productivity change, which was initially attributed to technological changes, i.e. shifts of the production or cost frontier. However, it became increasingly recognized after Nishimuzu and Page (1982) that productivity change can also be caused by changes in efficiency, that is, firms can move closer to the theoretical frontier over time, rather than showing genuine technological progress (shifts in the actual production frontier).

The Malmquist index (Malmquist 1953), introduced by the Swedish economist, Sten Malmquist, is a summary measure of the change in productivity of a given unit over time. Initially, Caves et. al. (1982) adapted this index in order to evaluate productivity movements between different production units. Later, Färe et al. (1989) derived the Malmquist productivity index as a geometric mean of the technologies of two periods of Caves et al. (1982)'s output productivity indices, and decomposed it into efficiency change and technological change components. Fare and Grosskopf (1992) then generalized their non-parametric approach to eliminate assumptions on optimizing behavior, efficiency, and the need for price data, and Fare et al. (1997) later used the technique to measure the productivity growth in healthcare across 10 OECD countries between 1974 and 1989.

In this article, we investigated the efficiency and technical changes in production as the initial step of a more comprehensive efficiency analysis of the two-stage healthcare system. This will enable us to pinpoint where exactly the inefficiencies occur and to determine the role of technology in this process. Additionally, non-discretionary inputs, which affect both the production and provision stages by shifting the frontiers, need to be controlled for.

The study mainly used OECD data (OECD Health Statistics 2015), which are, for the most part, standardized across fairly similar countries; so the quality of the variable measurements, although spotty at times, is relatively good. The only non-OECD data are the BMI figures acquired from the World Health Organization as a patient-risk characteristic. Inclusion of multiple (12) years also serves to give a better picture of each country, rather than a one-year snapshot.

Following the standard procedure, additional variables to control for non-discretionary inputs and the quality of outputs are used, which will be further investigated in the following pages. The aim here is to measure inefficiency levels, identify the sources of inefficiency, and measure the productivity growth and decompose the technical change from the changes in technical efficiency.

II. METHODOLOGY

2.1. Literature

Two methodologies are most common in the literature: DEA (Data Envelopment Analysis) and SFA (Stochastic Frontier Analysis). Both approaches use "frontier analyses" for measuring efficiency. Frontier analysis compares a firm's (e.g., hospital, physician practice) use of actual inputs and outputs to efficient combinations of multiple inputs and/or outputs. Although the two methods use different approaches to calculate the ''frontier'' of efficient combinations used for comparison, they are constructed using similar types of inputs and outputs, typically those in publicly available data. Both DEA and SFA require appropriate conceptualization of the relationship between the measured inputs and outputs.

In this study, we adopt the DEA methodology, which was first introduced by Charnes, Cooper, and Rhodes in 1978 (Charnes et al. 1978) and further formalized by Banker, Charnes and Cooper in 1984 (Banker et al. 1984) based on Farrell's (1957) simple measure of firm efficiency that accounted for multiple inputs. The first application of DEA to health issues is an unpublished work from 1979 regarding family planning centers in Costa Rica and Guatemala (Ray 2004). Nunamaker and Lewin (1983) is the first published work applying DEA to healthcare, whereas Sherman (1984) was the first author to use DEA to evaluate overall hospital efficiency.

Today there is a very extensive literature surveyed by O'Neill et al. (2008), who emphasize national differences in hospital efficiency research, and Ozcan (2008) who considers many aspects of healthcare delivery, as well as providing an overview of existing techniques. Hollingsworth (2008) classifies 317 published papers into various subcategories and offers comments as to their practical usefulness.

2.2. Output-Oriented Radial Model

As we are using panel data in this study, each yearly data point for each country is treated as a separate *decisin making unit* (DMU), assuming non-regressive technology. We adopt an output-oriented radial model with equiproportional changes in output to determine the overall efficiency where the system tries to maximize its output levels; given the input levels it is provided. We only focus on the technical efficiency side of the equation; which is necessitated both by theoretical and data considerations, as consistent international hospital cost statistics needed for the estimation of cost efficiency are not available.

2.3. Model Specification

DEA relies on a number of fairly weak assumptions to construct the production technology but avoids any explicit functional relationship between the inputs and outputs through a production function (Deb, Ray 2013). These assumptions are summarized below. Let Ψ be the feasible set:

a) all observed input-output combinations are possible; $(x_1, y_1) \in \Psi$.

b) the production possibility set is convex; Let $\alpha \in [0, 1]$; If (x_1, y_1), $(x_2, y_2) \in \Psi$, then $(x, y) = \alpha(x_1, y_1) + (1-\alpha)(x_2, y_2) \in \Psi$.

c) inputs and outputs are freely disposable; Let $x_2 \geq x_1$, and $y_2 \leq y_1$. If $(x_1, y_1) \in \Psi$ then $(x_2, y_1) \in \Psi$ and $(x_1, y_2) \in \Psi$

Let (x_i, y_i) represent the input-output bundle of a firm i, assuming input-output bundle observed for N firms. Then given the aforementioned assumptions, the CRS production possibility set is

$$\mathrm{T_c} = \{(\mathrm{x, y}); \mathrm{x} \geq \sum_i^N \lambda_i x_i ; \mathrm{y_i} \leq \sum_i^N \lambda_i y_i ; \lambda_i \geq 0; (i = 1,2,3,....,N)\} \qquad \{\mathrm{i}\}$$

By measuring the radial (equiproportional) efficiency levels of production under constant returns to scale (CRS), we obtain the efficient services (y*) that should have been produced. However, the convexity and the scalability of the control variables need to be addressed, because the quality (or risk) does not scale like the actual outputs, and these controls are subject to variable returns to scale (VRS) by definition, which further requires the condition $\sum_i^N \lambda_i = 1$ for controls, where q_{ik} is the control k for DMU i. The output-oriented radial efficiency of a DMU s:

$$\mathrm{TE}\ (\mathrm{x_s}, \mathrm{y_s}) = (\frac{1}{1+\beta_s}) \text{, where } \beta_s = \max(\beta) : (x_s, (1+\beta) y_s) \in \mathrm{Tc} \qquad \{\mathrm{ii}\}$$

The standard DEA LP problem solved to estimate the efficiency of DMU s, relative to contemporaneous CRS frontier is

Objective: Max β, subject to {iii}

∑λi xij ≤ x0j	j = 1…3	(Input constraint)	(1)
∑λiyik ≥ (1 + β) y0k	k = 1…3	(Output constraint)	(2)
∑λi qi1 ≤ qs1		(Quality constraint with undesirable outcome)	(3)
∑λi qi2 ≥ qs2		(Risk factors fused into one variable)	(4a)
∑λi qi3 ≥ qs3		(Control for inequality)	(4b)
λi ≥ 0		(Reference Selection)	(5)

β : Radial Output inefficiency

In the maximization problem above (Max β), constraints (1), (2), and (5) ensure that the benchmark unit created from the convex combination of actually observed data points does not use any more inputs (resources) than the comparison unit while producing β* y0k more outputs (services), where β is the radial inefficiency rate for all outputs. If β equals 0, then the unit appears efficient in producing at least at one output, given the observed data. The inclusion of undesirable output (3) in the first stage acts like a control variable and ensures that the benchmark unit created from the convex combination of reference DMUs, which produce β* y0k more output, has at least the same quality of healthcare.

We use Ruggiero's 3-stage method (Ruggiero 1998) to incorporate multiple risk factors into one risk variable (4a), as it performed best in virtually all scenarios, being the only model robust to sample size and the number of nondiscretionary variables (Muñiz et al. 2006). The original DEA model without the risk factors (4a) is solved and the second-stage regression on the risk factors is performed. Let $\hat{\beta}$ be the estimated inefficiency regressed on the risk factors:

$$\hat{\beta} = qi2 = \alpha + \gamma 1\ r1 + \gamma 2\ r2 + \gamma 3\ r3 + \varepsilon \qquad \{iv\}$$

After construction of qi2 (the combined patient-risk control) from estimating the first inefficiency, the model {iii} is solved again. Finally, inequality of access to healthcare enters the problem as yet another environmental variable that needs to be controlled for in the model. This is represented in the equation (4b), in a similar fashion to the risk factors, but introduced separately.

2.4. Malmquist Index and Measuring Technical Change

The assumption of "non-regressive technology" allows us to include all current and past observations in the calculation of inefficiency for a certain DMU. Let the calculated inefficiency of the input-output bundle of a country i with respect to technology…

…in year t = βit,t , and in year t+1 = βit,t+1

βit,t+1 ≥ βit,t implies that the measured inefficiency of a DMU through time will tend to increase. The inclusion of new observations due to additional years will inevitably bring in more efficient DMUs, shifting up the constructed production frontier, causing past DMUs to appear more inefficient, due to two possible reasons:

a) The actual production frontier shifts up (technological progress),

b) The constructed frontier moves closer to the actual frontier (increase in efficiency).

Let the average OECD inefficiency in year t measured in year t = $\sum_{1}^{n} \beta_{\mathrm{tt}}^{\mathrm{i}} / n$

$\sum_{1}^{n} \beta_{\mathrm{tt+1}}^{\mathrm{i}} / n \geq \sum_{1}^{n} \beta_{\mathrm{tt}}^{\mathrm{i}} / n$ implies that the measured average inefficiency for a certain year will tend to increase over time, inevitably shifting up the production frontier. This fact must be invariant to the base year "t", and thus $\sum_{1}^{n} \beta_{\mathrm{t\text{-}1t+1}}^{\mathrm{i}} / n \geq \sum_{1}^{n} \beta_{\mathrm{t\text{-}1t}}^{\mathrm{i}} / n$ must also hold.

In order to measure the productivity growth, we need to convert the inefficiency (β) values obtained in the DEA process to efficiency values (D) as in $D_{\mathrm{tt}}^{\mathrm{i}} = 1/(1+\beta_{\mathrm{tt}}^{\mathrm{i}})$.

Then, following Färe et al. (1992), we obtain the Malmquist productivity values and decompose them into technical change and efficiency change in the following way:

$$M_o(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{x}^{t},\mathbf{y}^{t}) = \frac{D_o^{t+1}(\mathbf{x}^{t+1},\mathbf{y}^{t+1})}{D_o^{t}(\mathbf{x}^{t},\mathbf{y}^{t})} \times \left[\left(\frac{D_o^{t}(\mathbf{x}^{t+1},\mathbf{y}^{t+1})}{D_o^{t+1}(\mathbf{x}^{t+1},\mathbf{y}^{t+1})}\right)\left(\frac{D_o^{t}(\mathbf{x}^{t},\mathbf{y}^{t})}{D_o^{t+1}(\mathbf{x}^{t},\mathbf{y}^{t})}\right)\right]^{1/2}$$

$$\text{technical change} = \left[\left(\frac{D_o^{t}(\mathbf{x}^{t+1},\mathbf{y}^{t+1})}{D_o^{t+1}(\mathbf{x}^{t+1},\mathbf{y}^{t+1})}\right) \times \left(\frac{D_o^{t}(\mathbf{x}^{t},\mathbf{y}^{t})}{D_o^{t+1}(\mathbf{x}^{t},\mathbf{y}^{t})}\right)\right]^{1/2}$$

$$\text{efficiency change} = \frac{D_o^{t+1}(\mathbf{x}^{t+1},\mathbf{y}^{t+1})}{D_o^{t}(\mathbf{x}^{t},\mathbf{y}^{t})}$$

III. DATA

Data used in this study are obtained from the Organization for Economic Cooperation and Development (OECD) Health Statistics, which is the broadest source of comparable statistics on diverse health systems across OECD countries. The dataset consists of 34 OECD countries and 12 years between 2000 and 2011 for a total of 408 decision making units (DMUs). The sources and methods of data collection are described in detail in the OECD documentation (Health at a Glance 2013; OECD Indicators 2015) though a slight adjustment of OECD data is unavoidable and common in OECD studies due non-uniform reporting practices (Retzlaff-Roberts et al. 2004).

The variables used to determine efficiency include: Inputs (resources), outputs (health services), quality of outputs (PYLL), patient risk characteristics, and inequality with access to healthcare (see Table 1).

3.1. Resources (Inputs)

The inclusion of physicians, nurses and hospital beds is standard across most healthcare studies and there is significant homogeneity in the data as well.

3.2. Health Services (Outputs)

We use three of the most commonly used hospital services, namely doctor consultations, hospital discharge rates, and patient days, as the intermediate goods, or the outputs of the first stage, later to be used as inputs of second stage. Because their homogeneity varies and effectiveness on health status depends on environmental variables, we control for per capita healthcare expenditure as a proxy for capital intensity, in addition to risk factors, and inequality.

3.3.Quality of Health Services (Control)

We are using Potential years of life lost (PYLL)* as a proxy for service quality at the first stage. It is defined as “a summary measure of premature mortality which provides an explicit way of weighting deaths occurring at younger ages, which are, a priori, preventable”.

* The calculations for PYLL involve adding up deaths occurring at each age and multiplying this with the number of remaining years to live up to a selected age limit. The limit of 70 years has been chosen for the calculations in OECD Health Data.

3.4.Patient-risk Characteristics (Control)

There are three highly standardized and commonly used risk characteristics defined in the OECD data set, namely tobacco and alcohol consumption, and obesity. Data regarding tobacco and alcohol consumption have been obtained from the OECD web site, while the BMI figures, as a proxy for overweight population, were obtained from the WHO data set (Global Health Observatory Data Repository 2015).

3.5.Inequality in Access to Healthcare (Control)

As a proxy for inequality of access to healthcare, the Gini coefficient and alternatively poverty rates for each country are used. Although not a perfect match, the Gini is a sufficient indicator of healthcare inequality.

Table 1. Variables

	#	Variables	Definition	Measurement
Resources	1	**Physicians**	Professionally active physicians, including practising physicians	density per 1 000 population
	2	**Nurses**	Professionally active nurses, including practising nurses	density per 1 000 population
	3	**Hospital beds**	Regularly maintained & staffed, immediately available for use	density per 1 000 population
Services	4	**Doctor consultations**	Number of contacts with physicians, all causes.	per capita
	5	**Hospital discharge rates**	Release of a patient who has stayed at least one night in hospital	per 100 000 population
	6	**Patient Days**	Number of days patients stayed in hospital, each at least 1 night	per 100 000 population
Risk factors	7	**Tobacco Consumption**	Tobacco consumption, % of all adult daily smokers	percentage of population
	8	**Alcohol consumption**	Alcohol consumption, litres per capita aged 15+	litres per capita aged 15+
	9	**BMI**	Overweight population, % of all population with a BMI>25 kg/m2	percentage of population
Ineq.	10a	**Gini Coefficient**	Measurement of Inequality in the population	between 0 and 1
	10b	**Poverty**	Percentage of population below poverty threshold	percentage of population
Qua.	11	**PYLL**	Potential Years of Life Lost, All causes, 0-69 Years	per 100 000 population

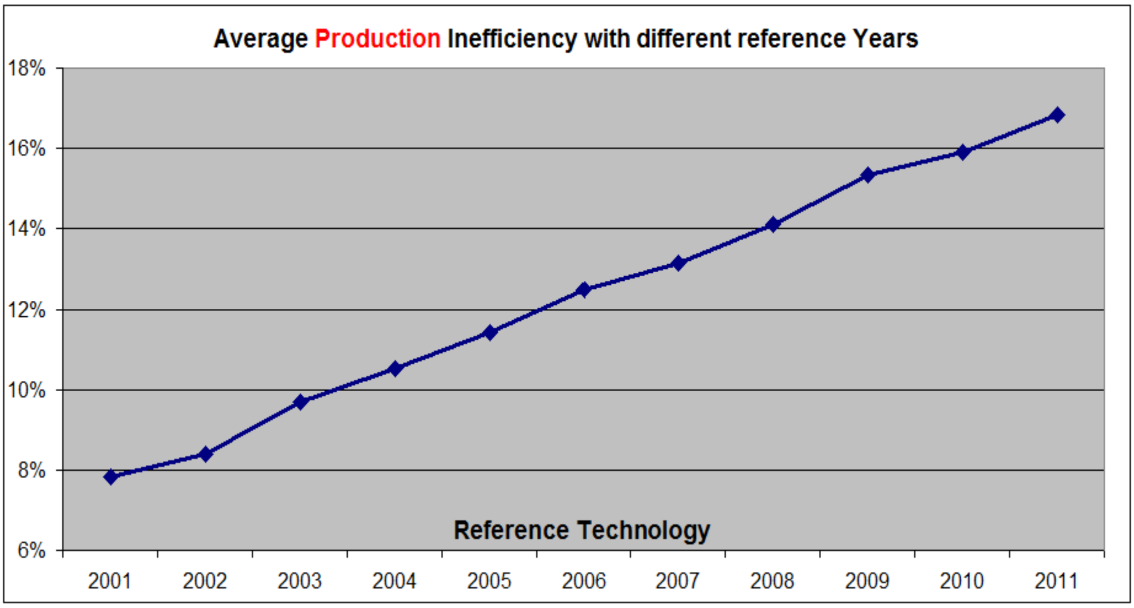
Source: OECD Health Statistics 2013 - Frequently Requested Data

IV. RESULTS

4.1. Productivity and Technical Change

The inclusion of the future observations inevitably increases the measured inefficiency for each year’s OECD average. As argued earlier, this is either because of technological progress, which is a shift in production frontier, or DMUs moving closer to the actual frontier and helping us construct a more realistic one. As we discussed above, the measured efficiency across time is fairly stable in the long run; therefore the bulk of technical change in the long run largely reflects technological progress.

When we look at the measured inefficiency figures for any base year (2001 to 2011), we find similar results which seem to be consistent and robust over time. In each of the cases, the evaluated year appears increasingly more inefficient due to the shifting frontier, albeit at slightly different levels (0.74% - 0.92%) due to short-run efficiency fluctuations as well as measurement issues with respect to the observed data. Long run averages, however, seem to agree with each other, at around 0.82%.



Graph 1. Productivity Growth and Inefficiency Path over the Years

Table 2. Inefficiency of Year i (left) with Respect to The Technology of Year j (top)

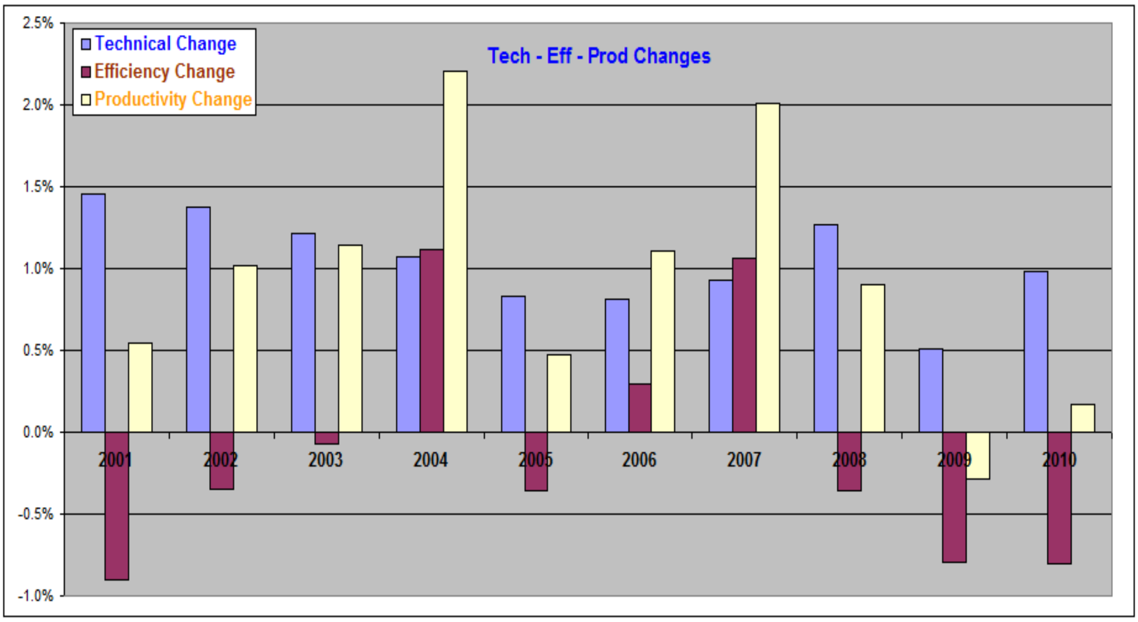
OECD (%)	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	Annual
2011	4.31	4.59	5.31	5.64	6.30	7.45	8.25	9.76	11.65	12.12	13.11	0.80
2010	4.56	4.84	5.68	5.99	6.91	8.39	9.15	10.30	11.83	12.20	13.42	0.81
2009	5.08	5.38	6.52	6.96	7.74	8.84	9.27	10.08	11.31	12.07	13.18	0.74
2008	5.83	6.23	7.43	8.36	8.92	9.76	10.25	10.91	12.48	13.04	13.87	0.73
2007	6.64	7.08	8.54	9.14	10.54	11.35	12.09	13.51	14.80	15.64	16.25	0.87
2006	7.38	7.67	9.40	10.59	11.68	12.42	13.49	14.48	15.59	16.11	17.50	0.92
2005	8.27	8.70	9.85	10.46	12.02	13.14	14.01	14.87	15.74	16.50	17.33	0.82
2004	10.13	10.39	11.52	13.26	14.10	15.28	16.12	16.94	18.07	18.47	19.08	0.81
2003	10.94	11.47	13.19	14.17	14.81	15.92	16.83	17.54	18.40	18.80	19.73	0.80
2002	11.06	12.79	14.14	15.24	16.05	17.04	17.43	18.27	19.31	19.86	20.76	0.88
2001	11.77	13.29	14.83	15.77	16.56	17.55	17.88	18.47	19.52	20.12	20.85	0.82

Table 3. Decomposition of Productivity Growth, Technical and Efficiency Changes

OECD	Tech.Chng (%)	Eff.Chng (%)	Prod.Chng (%)
Average	8.46	-1.18	7.18
2001	1.46	-0.90	0.54
2002	1.37	-0.35	1.02
2003	1.21	-0.07	1.14
2004	1.07	1.11	2.20
2005	0.83	-0.36	0.47
2006	0.81	0.29	1.11
2007	0.93	1.06	2.00
2008	1.26	-0.36	0.90
2009	0.51	-0.79	-0.29
2010	0.98	-0.80	0.17

Cumulative productivity growth between 2001 and 2011 is 7.2% on average, somewhat less than the technical change at 8.5%, due to a slight decrease in technical efficiency, by around 1.2%. It is then plausible to assume that fluctuations are mostly due to short run changes in efficiency although the long run efficiency patterns seem to be relatively stable, as shown in the following graph 2.

Annual efficiency changes clearly take time to adjust. Whenever there is a significant change in technology, it leads to a disruption in the system and a temporary decrease in efficiency, which is then followed by a sequential increase and so on. In the long run, however, those fluctuations tend to smooth out. Productivity growth, integrating the inefficiency changes, clearly demonstrates these fluctuations, having a much greater variance than technical change, and sometimes going negative. Technical change however, is always positive (being non-regressive) and relatively stable (between 0.51% - 1.46%) though we see a slight decreasing trend. Considering the measurement errors in individual years, the fluctuations in technical change are likely even smaller, and from our study, it is not clear whether the technical change is increasing or decreasing.



Graph 2. Decomposition of Productivity Growth, Technical and Efficiency Changes

Table 4. Countries with the highest cumulative technical change 2000-2011

Highest Techn. Change 2001-2011		
1	Mexico	52.20%
2	Netherlands	22.54%
3	Portugal	21.96%
4	Denmark	19.44%
5	France	19.75%
6	Slovak Republic	19.34%
7	United States	14.92%
8	Luxembourg	12.92%
9	Finland	12.23%
10	Belgium	11.74%

Countries with the highest technical change between 2001 and 2011 are mostly those which spend the most on healthcare and invest in technology. However, there are a few unexpected entries among the top countries such as Mexico and Slovak Republic, which seem to be rapidly catching up to their more developed neighbours. We should also note that all those countries also suffer from high inefficiency; none of the relatively efficient countries are among the top countries. This implies the technical change for relatively more efficient countries is underestimated in the analysis.

4.2. Limitations of The Study

a) Radial efficiency analysis tends to underestimate the inefficiency: The radial efficiency approach assumes no substitution or trade-off between outputs and adopts a conservative way to determine the efficiency levels. The results should be evaluated with the slacks in mind. The countries with no slacks are usually in much better shape than those with large slacks.

b) Frontier analysis tends to underestimate technical changes: There are two reasons for this; 1) technical changes for the efficient countries on the production frontier are inherently underestimated, 2) technical spill-overs between countries do not shift the frontier but increase the efficiency through catch-up, which underestimates the role of technical change.

c) Production efficiency is just one part of the healthcare efficiency and only partially addresses the overall of the healthcare sector. Efficiency in provision as well as losses due to non-discretionary inputs (such as inequality) and lack of sufficient spending need to be considered. Some countries which excel at one particular stage often fail in another, and it is crucial to identify the exact sources of inefficiency.

4.3. Conclusion and Discussion

Following the steps of Fare et al. (1997), who examined the technical change in OECD countries in the 1974 - 1989 period and found a cumulative 33% growth with only 10 developed countries, our study investigated whether the technological progress still persists in the modern era, and found supporting results. Unlike the bulk of the literature, all of the 34 OECD countries are included in the study, which found about 8.5% cumulative technical change and 7.2% productivity growth between 2001 and 2011. The technical change has slightly speeded up in recent years and most of the fluctuations seem to be due to the efficiency changes as a result of the catch-up process.

Given the aforementioned limitations of the methodology, the technical change is likely to be underestimated. Concentrating on the more developed countries boosts the annual technical change from 0.82% to around 1.2%. Therefore, it is plausible to assume a 1% annual technical change, which would accumulate to 16% in 15 years. Limiting the results to relatively more developed nations, on the other hand, as in Färe et al (1997), would imply about 20% of cumulative change at the same time frame. The more comprehensive nature of our study and the spillover effects that are not typically detected in the analysis imply even larger technical change.

Although investment in technology is partially responsible for increasing healthcare costs, it more than pays back as it is also the main driver of the productivity increases. This study, however, only deals with the production side of the story and calculates the technical change for health services, which are intermediate goods in the healthcare system. The ultimate goal of the healthcare system, however, is to produce the best health outcomes.

We will devise a more coherent multi-stage framework in subsequent studies to further investigate and establish a clear link between output and outcome productivity growth and technical changes. This will also help us to better analyse the impact of technical changes on health outcomes, and whether the inefficiencies in the production of services reveal themselves as inefficiencies in health outcomes.

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Atıfta Bulunmak İçin / Cite This Paper:

Bekaroğlu, C. & Heffley, D. (2018). The Impact of Technical Change on Healthcare Production and Efficiency**.** *Hacettepe Journal of Health Administration*, 21(4), 641-653.