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Determinants of health sector efficiency: evidence from a two-step analysis on 30 OECD countries

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Abstract

This study aims to assess the efficiency of expenditure on health in 30 OECD countries over the period 2005-2015 by regressing Data Envelopment Analysis (DEA) output efficiency scores on discretionary and non-discretionary variables, with a two-stage DEA/Tobit and bootstrap procedure. We show that health inefficiency in OECD countries is related to per capita GDP, vaccine coverage and tobacco consumption, also controlling for geographical and institutional variables (i.e., bureaucratic red tape and weather temperature).

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1. Introduction

The attainment of more efficient health care systems has always been a central goal for policy makers. Also due to the 2007/2008 economic crisis, the need to rationalize public expenditure (i.e., spending review policies) across all government functions has been furtherly exogenously reinforced. Considered that during the last forty years health care expenditure (as a share of the GDP) has rapidly increased up to 13.3% in 2016 in OECD countries, the achievement of a more sustainable health care system has become a priority target for policy makers.

On this ground, the aim of our work is twofold: a) to pin down the main determinants of health care systems efficiency (HHS) by focusing on the impact of discretionary and non-discretionary factors; b) to highlight areas of possible efficiency enhancements.

A substantial body of empirical literature focuses on the measurement of health sector performance across different OECD (see Mobley and Magnussen 1998, Hollingsworth 2003, Osterkamp 2004, Retzlaff-Roberts *et al*. 2004, Bhat 2005, Afonso *et al*. 2005, Grosskopf *et al*. 2006, Siciliani 2006, Hollingsworth 2008, Spinks and Hollingsworth 2009, Adam *et al*. 2011, Mirmirani and Lippmann 2011, Sinimole 2012, Cetin and Bahce, 2016, Carrillo and Jorge 2017, Ozcan and Khushalani 2017), EU (see Afonso *et al*. 2010a, Jeremic *et al*. 2012 and Del Rocio Moreno-Enguix *et al*. 2018) and emerging countries (see Herrera and Pang 2005 and Afonso *et al*. 2010a) using a wide set of socio-economic indicators. In terms of methodology, most of this stream of literature estimates the extent of slack in government expenditures by employing, alternatively or in combination, Free Disposable Hull – FDH (see Deprins *et al*. 1984) and Data Envelopment Analysis – DEA (see Farrel 1957 and Charnes *et al*. 1978) nonparametric production frontier techniques, ensuring the least amount of possible restrictions on data. Besides this stream of works, others add parametric techniques (i.e., stochastic frontier analysis, SFA) to former nonparametric methods (see Greene 2004, Greene 2010, Kumbhakar 2010, Varabyova and Schreyögg 2013, de Cos and Moral-Benito 2014 and Hamidi and Akinci 2016). Other authors (see Spinks 2009), however, highlight the possible pitfalls and limitations that affect such methods.

Closer to our approach, in terms of methodology adopted and research question raised, is a second stream of literature (see Puig-Junoy 1998, Evans *et al*. 2001, Afonso and St. Aubyn 2011, Wranik 2012 and Hadad *et al*. 2013) that employs a two-stage estimation strategy. This type of analysis is grounded on a combination of nonparametric and parametric methods: in the first stage, the relative production efficiency analysis is conducted through non-parametric techniques, such as FDH and DEA; while in the second-stage, Tobit, Truncated and Bootstrap regression analysis is adopted in order to investigate the relation between health care systems efficiency scores and "environmental" variables.

Varabyova and Müller (2016) conducted a systematic review and a meta-analysis on the works that investigate the efficiency of health care systems in OECD countries, assessing that international comparisons of health care system efficiency can potentially provide a rich source of evidence and therefore influence policy decisions by outlining directions for reforms. They conclude that measuring the efficiency of health care provision by considering a comparable sample of countries is useful to detect the areas in which there is an improvement potential in the use of resources.

Among the others, Hadad *et al*. (2013), using a panel of 31 OECD countries, employs a two-stage DEA and multivariate regression analysis. In the first stage, the HSS is assessed by relying on two different input/output specifications, based on, respectively, relative more discretionary and non-discretionary inputs. In the second stage, through a multivariate regression analysis he checks if institutional arrangements, population habits and socioeconomic determinants reveal an explanatory capacity over HHS. The main findings exhibit an ambiguous incidence of the socio-economic and environmental regressors.

Very close to ours, Afonso e St. Aubyn (2011), spanning through a panel of 21 OECD countries, employ a two stage DEA and Tobit/Bootstrap estimation strategy. In the second stage, they mainly investigate the incidence exerted by non-discretionary variables on HHS. The main findings reveal that inefficiency in health is strongly explained by factors that in a short period span are not under the control of governments.

In this context, we perform a two-stage FDH/DEA and Tobit analysis, also adopting the Simar and Wilson (2007) algorithm#1 bootstrap procedure, in order to ensure non-biased estimates. We highlight the main differences and improvements with respect to previous literature. With regard to the first stage, we employ one input, public health expenditure, measured in monetary terms, as in Afonso *et al*. (2005) and Gupta and Verhoeven (2001) but differently from Afonso and St. Aubyn (2005), where inputs are measured in physical terms. As for the output measure, we build a new health performance indicator (HPI) that is composed, besides health status indicators (i.e., infant mortality rate and life expectancy at birth), as in Afonso and St. Aubyn (2011), Afonso *et al*. (2005), and Gupta and Verhoeven (2001), also by a health treatment variable (i.e., hospital discharges). With respect to the second stage, we extend the analysis of the role of non-discretionary factors (see Afonso and St. Aubyn 2011), including new variables such as vaccine coverage for elderly individuals and weather temperature, besides the more traditional life-style habits controls. Our main findings reveal that vaccine coverage, weather temperature, GDP and tobacco consumption are strongly correlated to inefficiencies in the health sector. In terms of policy implications, with respect to discretionary inputs, our results confirm the existence of a wide room for efficiency improvements.

The remainder of the manuscript is structured as follows. Section 2 reports data and variables used in the analysis. Section 3 describes the methodology and the estimation strategy. Section 4 presents the estimation results. Finally, section 5 draws the main concluding remarks.

2. Data section

We use data from a panel of 30 OECD countries for a period of 11 years, from 2005 to 2015. The sample is composed by: Australia, Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Luxembourg, Netherlands, New Zealand, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom. We use averages, instead of higher frequency data; this is preferable for different reasons. First, the effect of some policies is not immediately observable, but may take time to settle in. Second, most of the measures of government activity have long-run effects.

For the first stage of the analysis (FDH analysis and DEA) we use the variables (source: OECD) reported in Table I.

Table I: – DEA/FDH variables description and sources

Variables	Description	Source
Infant Mortality Rate (IMR)	Number of deaths under one year of age occurring among the live births in a given geographical area during a given year, per 1,000 live births occurring among the population of the given geographical area during the same year. In other terms, IMR is equal to (Number of children who died before 12 months) / (Number of born children) x 1,000	OECD
Life Expectancy at birth (LE)	How long, on average, a new-born can expect to live, if current death rates do not change. This indicator is measured in years	OECD
Hospital Discharge rates (HD)	Number of patients who leave a hospital after receiving care. Hospital discharge is defined as the release of a patient who has stayed at least one night in hospital. It includes deaths in hospital following inpatient care. Same-day discharges are usually excluded. This indicator is measured per 100,000 inhabitants	OECD
Health Expenditure (HE)	Final consumption of health care goods and services (i.e., current health expenditure) including personal health care (curative care, rehabilitative care, long-term care, ancillary services and medical goods) and collective services (prevention and public health services as well as health administration) but excluding spending on investments. Health care is financed through a mix of financing arrangements including government spending and compulsory health insurance ("Government/compulsory") as well as voluntary health insurance and private funds such as households' out-of-pocket payments, NGOs and private corporations ("Voluntary"). This indicator is presented as a total and is measured in USD per capita (using economy-wide PPPs)	OECD

The first three variables are interpreted as output, reflecting health status and health outcomes; per capita Health Expenditure represents our input.

Table II shows the descriptive statistics of the variables used in the FDH analysis and in the DEA.

Table II: Descriptive statistics for the non-parametric analysis

	Mean	SD	Max.	Min.
Infant Mortality Rate (IMR)	3.47	1.61	10.70	1.60
Life Expectancy at birth (LE)	80.74	2.32	83.90	74.60
Hospital Discharge rates (HD)	16475.94	3738.21	25581.10	10917.40
Health Expenditure (HE)	3097.67	1334.77	6147.97	856.95
Discounted Health Expenditure (DHE)	2706.20	1031.34	4918.38	771.26

Source: OECD and World Bank.

Note: all variables are collected for years 2005 and 2015 and averaged, except for IMR, available until 2014 for Korea and until 2013 for New Zealand; HD, available until 2014 for Australia, France e New Zealand and until 2010 for Greece and Netherlands.

The econometric specification in the second stage of the analysis grounds on the set of variables reported in Table III.

Table III: – Econometric estimations variables description and sources

Variables	Description and motivation	Source
Gross Domestic Product (GDP)	Measured as PPP per capita GDP averaged over the period 2005-2015 (OECD data); the correlation sign of this variable with efficiency is ambiguous; per capita GDP can be positively correlated to the efficiency score since it proxies the physical capital stock, which favours production efficiency as well as monitoring of policymakers (see Afonso and St. Aubyn 2011); or negatively related, via the Balassa (1964)-Samuelson (1964) effect.	OECD
Weather Temperature (TEMP)	Measured as the average temperature over the period 2006-2010. This variable is a country specific exogenous variable that may be positively correlated to life expectancy at birth (World Bank, Climate change knowledge portal). Not included in previous health care efficiency empirical papers.	World Bank
Red Tape (RT)	Measured as the average value of the survey indicator GCI over the period 2007-2015. This indicator measures the slowness of bureaucracy in implementing public policies and it can be used as a proxy for institutional framework inefficiency.	GCI[1]
Vaccine coverage – Preventive health care		
Influenza Vaccine 65+ (VAX65)	Measured as the percentage of the population aged 65 and older who has received an annual flu vaccine. This variable can also be a proxy for the willingness of elderly individuals to demand preventive health care (OECD data, https://data.oecd.org/health care/influenza-vaccination-rates.htm).	OECD
Diphtheria, Tetanus, and Pertussis Vaccine (DTP)	Measured as the percentage of children who receive at least one dose of DTP vaccine at around age 1. This variable (used also in Herrera and Pang 2005) accounts for preventive health care treatments of infant individuals (OECD data, https://data.oecd.org/health care/child-vaccination-rates.htm).	OECD
Lifestyle factors		
Tobacco (TOB)	Measured as the percentage of population aged 15 years old and over reporting to be daily smokers (OECD Data, https://data.oecd.org/healthrisk/daily-smokers.htm). This variable exerting a negative impact on LE is expected to be inversely related to efficiency scores, as in previous works (see Afonso and St. Aubyn 2011).	OECD
Obesity (OB)	People with excessive weight present health risks because of the high proportion of body fat. This indicator is derived from "self-reported" data (estimates of height and weight from population-based health interview surveys) and is measured as a percentage of the population aged 15 years and older. Lifestyle regressor included in previous works (see Afonso and St. Aubyn 2011) for testing the effect on DEA/FDH efficiency scores (OECD Data, https://data.oecd.org/healthrisk/overweight-or-obese-population.htm).	OECD

These variables, that might be correlated to efficiency, are non-discretionary or exogenous factors, since they cannot be changed by the policymaker in the short run.

[1] The GCI measures the performance of the public sector and varies from zero (worst) to 100 (best). It analyses competitiveness along 12 pillars: institutions, infrastructure, macroeconomic environment, health and primary education, higher education and training, goods market efficiency, labour market efficiency, financial market development, technological readiness, market size, business sophistication and innovation.

These are, in turn, organized into three sub-indices in line with three main stages of development: basic requirements, efficiency enhancers, and innovation and sophistication factors. The three sub-indices are given different weights in the calculation of the overall index, depending on each economy's stage of development, as proxied by its GDP per capita and share of exports represented by mineral raw materials (https://tcdata360.worldbank.org/indicators/gci?country=BRA&indicator=631&viz=line_chart&years=2007,2017).

Table IV: Descriptive statistics for the regressors of the econometric specification

	Mean	SD	Max.	Min.
Gross Domestic Product (GDP)	35670.67	13351.51	87881.00	18195.00
Influenza Vaccine 65+ (VAX65)	41.57	22.78	81.70	1.60
Weather Temperature (TEMP)	10.35	4.38	21.92	2.32
Diphtheria, Tetanus, and Pertussis Vaccine (DTP)	96.17	2.26	99.00	92.00
Red Tape (RT)	3.28	0.64	4.49	2.09
Tobacco (TOB)	19.46	4.23	27.30	10.90
Obesity (OB)	16.27	5.17	30.00	2.80

Source: OECD (GDP, VAX65, DTP, TOB, OB), World Economic Forum (RT) and World Bank (TEMP).

Note: all variables are collected for years 2005 and 2015 and averaged, with the exception of *(i)* TOB, available until 2014 for Austria, Belgium, Estonia, France, Greece, Hungary, Israel, Latvia, Poland, Portugal, Slovak Republic, Slovenia, Spain, and Turkey, until 2013 for Australia and Germany, and until 2012 for Switzerland; *(ii)* OB, available until 2014 for Austria, Belgium, Czech Republic, Denmark, Estonia, France, Germany, Greece, Hungary, Israel, Latvia, Luxembourg, Poland, Portugal, Slovak Republic, Slovenia, Spain, Turkey, and United Kingdom and until 2007 for Australia; *(iii)* VAX65, available until 2014 for Austria, Czech Republic, Greece, Japan, Poland, and Turkey, until 2013 for Belgium, until 2012 for Switzerland and until 2009 for Australia.

3. Methodology and estimation strategy

In order to pin down the determinants of health sector efficiency, our approach entails a two-stage estimation strategy (see Afonso *et al*. 2005, Afonso and St. Aubyn 2005, Afonso *et al*. 2010a and 2010b, and Afonso and St. Aubyn 2011). In the first stage, we construct a Health Performance Indicator (HPI), based on IMR, LE and HD variables, that represents our output indicator, against which we measure countries' relative efficiency in the use of the input variable (HE). We adopt a non-parametric approach (FDH analysis and DEA).

In the second stage, we implement a censored Tobit regression estimation in order to investigate the causal relationship between the estimated countries' efficiency scores and a set of institutional, socio-economic, lifestyle and geographical characteristics.

Furtherly, we estimate the Simar and Wilson (2007) algorithm#1 in order to account for the possibility of a correlation pattern among the estimated efficiency scores: errors may not be *iid* across countries and efficiency scores could thus take value 1, according to FDH and DEA linear formulation, with zero probability.

3.1 First stage: Efficiency analysis

3.1.1 The Health Performance Indicator (HPI)

We start by building up a Health Performance Index (HPI)[2], summarizing the output of health policies. As in Afonso and St Aubyn (2011) we consider health status indicators (IMR and LE); however, we also add a health treatment indicator (HD) as a proxy for patients' hospital care. To ensure that the highest values of the indicator are representative of the best performance, we

[2] We use the term performance to refer to the effectiveness of the health care service provision (i.e., the outcome achieved by the countries included in our panel). The concept of performance is a multidimensional concept related to both efficiency and effectiveness of public policies. We use the term performance to summarize the outcome achieved in the health sector by the countries selected for our analysis.

transform primary data on Infant Mortality Rates into Infant Survival Rates (ISR) by applying the following expression:

$$ISR = (1000\text{-}IMR)/IMR \tag{1}$$

which represents the ratio of children that survived the first year to the number of children that died.

Following Antonelli and De Bonis (2017, 2018 and 2019), each variable is normalized in the following way:[3]

$$0 \le P_{i,j} = \frac{x_{i,j} - x_{i,\min,j}}{x_{i,\max,j} - x_{i,\min,j}} \le 1, \quad i=1, 2 \ldots 30 \quad j=1, 2, 3 \tag{2}$$

where $x_{i,j}$ is the value of the output-variable j in country i, while $x_{i,minj}$ and $x_{i,maxj}$ represent, respectively, the minimum and maximum values for the same output-variable within the group of the 30 OECD countries. Each normalized variable ranges between 0 and 1 and higher values indicate a better relative performance. Finally, an overall indicator for the health sector performance is obtained as the sum of the partial indicators coherently with the existing literature (see Afonso and St Aubyn 2011). For country i we thus have:

$$HPI_i = \sum_{j=1}^{3} P_{ij} \tag{3}$$

3.1.2 FDH and DEA approach

We now turn to the measure of health sector efficiency employing the FDH and DEA[4] non-parametric methods. Both techniques allow to build a production possibility frontier, that enables the ranking of the countries' efficiency performances. DEA adds the hypothesis of convexity of the production possibility frontier. The performance achieved in the health sector (HPI) is the output, while health expenditure (HE) is the input.

We test, for each i country, the following general functional relationship:

$$HPI_i = f(HE_i), \; i = 1, \ldots, 30 \tag{4}$$

with $HPI_i < f(HE_i)$ denoting that country i is inefficient.

Countries on the frontier exhibit the highest possible level of performance, given the level of health expenditure (alternatively, they use the lowest level of expenditure to achieve a given level of performance); in other words, there exist no other countries that obtain the same level of performance with a lower level of expenditure. Countries on the frontier are assigned input and output efficiency scores of 1; against them, one can measure the relative input and output inefficiency of countries that lie inside the frontier, thus obtaining a relative ranking.

So, for each country, that represents a single decision-making unit (DMU) in the FDH/DEA method, the linear programming model is configured as to determine the level of input contracted efficiently in order to achieve the same output level.[5] We focus our attention on the input-oriented specification, since in many countries public finance constraints often impose a spending review process to limit resource waste in the health sector.

Then, the efficiency score for the *i-th* DMU is given by the solution of the following problem:[6]

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[3] We apply the same methodology used for the Human Development Indices. Methodological notes are available at the following link: http://hdr.undp.org/en/content/calculating-indices.

[4] See Deprins *et al.* (1984) for the Free Disposal Hull (FDH) method, and Farrell (1957) and Charnes *et al*. (1978) for the Data Envelopment Analysis (DEA).

[5] This is the input-oriented formulation of the problem. The output-oriented approach of the linear programming problem is configured to determine a DMU's potential output given its inputs.

[6] The problem is an input-oriented specification for variable returns to scale (vrs) in the equivalent envelopment form of the original linear programming problem as in Charnes *et al*. (1978).

$$
\begin{gathered}
Min_{\delta_i \lambda}\ \delta_i \\
\text{subject to } \delta y_i + Y\lambda \geq 0 \\
-x_i + X\lambda \geq 0 \\
n1'\lambda = 1 \\
\lambda \geq 0
\end{gathered} \tag{5}
$$

where **X** and **Y** are, respectively, the output matrix (m x n) and the input matrix (k x n), δ is the scalar ≤1 representing the distance between each country *i* and the frontier, defined as a linear combination of the best practice observations. The vector λ is a vector of constants representing the weights to be used to compute the linear combinations of the *peers* for the *i*-th country, thus indicating the attainable position on the frontier with an improvement of its efficiency. Finally, in the DEA case, if health has an inverted U-shape relationship with respect to health expenditure (see Culyer and Wagstaff 1993), the constraint n1'λ = 1 guarantees convexity of the frontier, accounting for variable returns to scale (see Banker *et al*. 1984).

3.2 Second stage: TOBIT regression estimations

As a second step of the empirical investigation, we assess the effects of some environmental and life-style variables on efficiency. The analysis considers "non-discretionary" variables as most of the literature on efficiency of the public sector (see Evans *et al*. 2001, Afonso *et al*. 2005, Afonso and St. Aubyn 2005, Afonso *et al*. 2010a and 2010b). Actually, variables other than the health expenditure level (our input) might be correlated with efficiency (our output), thus contributing to explain differences in the level of output (HPI) obtained per unit of money used, or, in other words, to pin down the reasons why some countries appear to need more resources than others do to obtain the same level of performance. The inclusion of "non-discretionary" variables in the econometric strategy is mainly due to the evaluation of their exogenous influence on the design and the effects of social policies (see Ruggiero 2004).

To this purpose, we start by estimating a Tobit regression model, since the distribution of the efficiency scores is not normal and is censored at 1 (as for its maximum value), grounding on the following specification:

$$EFF_i = \beta_1 GDP_i + \beta_2 VAX65_i + \beta_3 TEMP_i + \beta_4 DTP_i + \beta_5 RT_{i+}\ \beta_6 TOB_i + \beta_7 OB_i + \mathcal{E}_i,\ i = 1, \ldots, 30 \tag{6}$$

where EFF_i is the vector of the FDH input efficiency scores[7] while the regressors, on the right-hand side, have been described in section 3. The β_i are the coefficients to be estimated and $\mathcal{E}_i$ is the errors' vector. On the ground of previous empirical research and theoretical hypotheses, we expect a positive sign for DTP, and VEG; a negative sign for RT, TOB and OB; while previous results are more ambiguous for GDP. Moreover, we introduce two new variables, TEMP and VACC65, in order to verify country specific non-discretionary controls related to climate environment and preventive care for elderly individuals.

The two-stage FDH/DEA and Tobit method, however, can be biased in small samples. As pointed out by Simar and Wilson (2007), the estimation through DEA/FDH of the distance (HPI_i, HE_i) is affected by finite sample bias and efficiency scores are biased towards 1. Thus, performance scores are jointly calculated and the error term in (6) is serially correlated; moreover, non-discretionary variables are correlated to the efficiency scores and the error term.

[7] We use FDH input efficiency scores because in most of the analysed OECD countries the political debate on the health system is mainly focused on policy options that rely on expenditure's cuts (i.e., our input). Moreover, we prefer FDH to DEA since it is grounded on less restrictive assumptions. Results, however, do not change significantly by using output efficiency scores and/or the DEA method.

In order to deal with these pitfalls and possible misleading outcomes, we switch to bootstrapping methods, that, entailing an alternative data generating process for the estimation of the parameters, grants the attainment of unbiased results. In this vein, we employ one of the bootstrap estimation procedures proposed by Simar and Wilson (2007), namely algorithm #1 with 1,000 replications: the influence of non-discretionary inputs is estimated by a truncated linear regression and the significance of estimated coefficients is assessed by bootstrapping. This step is important in our strategy ensuring a robustness check of previous Tobit estimation outcomes.

4. Empirical analysis and robustness check

We start our empirical analysis calculating the values of the HPI for the year 2015, reported in Table V. The final values are characterized by a high degree of heterogeneity within the group of countries considered, ranging from 0.7882 (Turkey) to 2.1916 (Slovenia). The sample of countries appears to be balanced in relation to the performance indicator: 15 countries have an HPI higher than the average value; Belgium is in line with the average; the remaining 14 countries are placed under the average.

We then move to investigate the relationship between the output (as summarized by the HPI) and the input (represented by HE) of countries' health sectors calculating their efficiency scores. We use the average values of health expenditure over the period 2005-2015 to account for possible lagged effects of expenditure on output. Table VI summarizes the input-oriented efficiency scores. The efficiency analysis shows that Estonia, Korea, Latvia, Poland, Slovenia and Turkey are on the FDH frontier. Marginal differences characterize the DEA analysis due to the additional hypothesis of convexity.[8] On average, the efficiency score is about 0.7 for the FDH analysis and 0.6 for the DEA. This means that, on average, countries in the sample could obtain the same performance by reducing the input (HE) by about 30-40%. For the inefficient countries, the FDH scores ranges from 0.299 and 0.978 and the DEA scores from 0.270 and 0.940.

Moreover, according to their position with respect to the average per capita HE of our sample, we cluster two groups of countries (Table VI). With both methods we note that countries with per capita HE below the average displace relative higher efficiency scores with respect to the sample. The opposite is true when considering countries with higher than average per capita HE. This result can motivate further considerations in terms of the trade-off between efficiency and equity. As in van Doorslaer *et al*. (2000), this could reveal that countries with higher HE ensure a more capillary extension of the health care services.

[8] Note that in the DEA frontier a smaller number of countries is located on the frontier.

Table V: The Health Performance Index (2015)

Countries	LE	ISR	HD	HPI
Australia	0.8495	0.4121	0.4475	1.7090
Austria	0.7204	0.4311	1	2.1515
Belgium	0.6989	0.3943	0.3863	1.4795
Czech Republic	0.4409	0.5767	0.6629	1.6805
Denmark	0.6667	0.3326	0.2631	1.2624
Estonia	0.3333	0.5767	0.4248	1.3348
Finland	0.7527	0.9308	0.3892	2.0727
France	0.8387	0.3326	0.5075	1.6789
Germany	0.6559	0.3943	0.9968	2.0470
Greece	0.6989	0.2945	0.5952	1.5887
Hungary	0.1183	0.2721	0.6199	1.0103
Iceland	0.8495	0.6793	0.0319	1.5607
Ireland	0.7419	0.3775	0.2146	1.3340
Israel	0.8065	0.4311	0.3391	1.5766
Italy	0.8602	0.4729	0.0640	1.3971
Japan	1.0000	0.7200	0.1020	1.8220
Korea	0.8065	0.5210	0.3748	1.7022
Latvia	0.0000	0.2830	0.5310	0.8140
Luxembourg	0.8387	0.4961	0.2489	1.5837
Netherlands	0.7527	0.3943	0.0497	1.1966
New Zealand	0.7634	0.2004	0.2364	1.2002
Poland	0.3226	0.2945	0.4119	1.0290
Portugal	0.7097	0.4729	0	1.1826
Slovak Republic	0.2258	0.1931	0.6230	1.0419
Slovenia	0.6774	1	0.5142	2.1916
Spain	0.9032	0.5210	0.0353	1.4595
Sweden	0.8280	0.5767	0.2997	1.7044
Switzerland	0.9032	0.3066	0.4248	1.6346
Turkey	0.3656	0	0.4226	0.7882
United Kingdom	0.6882	0.3066	0.1550	1.1497

Note: our elaboration on OECD Health Statistics (2015). For the calculation of ISR we used 2014 data for Korea and 2013 data for New Zealand. For hospital discharges we used 2014 data for Australia, France and New Zealand; 2010 data for Greece and the Netherlands.

Table VI: FDH and DEA: input-oriented efficiency scores (2015)

Countries	FDH	DEA
Australia	0.648	0.496
Austria	0.553	0.543
Belgium	0.487	0.392
Czech Republic	0.978	0.907
Denmark	0.324	0.308
Estonia	1	1
Finland	0.692	0.652
France	0.496	0.459
Germany	0.542	0.504
Greece	0.778	0.678
Hungary	0.804	0.663
Iceland	0.528	0.452
Ireland	0.318	0.318
Israel	0.897	0.775
Italy	0.627	0.474
Japan	0.692	0.568
Korea	1	0.940
Latvia	1	0.795
Luxembourg	0.311	0.270
Netherlands	0.299	0.271
New Zealand	0.466	0.423
Poland	1	0.838
Portugal	0.554	0.495
Slovak Republic	0.778	0.620
Slovenia	1	1
Spain	0.687	0.546
Sweden	0.580	0.443
Switzerland	0.332	0.299
Turkey	1	1
United Kingdom	0.439	0.383
Average EFF all countries	0.660	0.584
Average EFF by countries' cluster		
Countries with HE < average HE	0.838	0.719
Countries with HE > average HE	0.483	0.449

Finally, we estimate a Tobit model to disentangle potential heterogeneity across countries that may affect the efficiency scores. We consider variables, other than the level of expenditure, that might affect efficiency though being beyond the policymakers' control in the short and medium run. Results are reported in Table VII.

Table VII: Regression results. Dependent variable: FDH input-oriented efficiency scores

Tobit regression with FDH efficiency scores		
	Model 1 FDH	Model 2 FDH
TEMP	0.0189431** (-0.0273)	0.0244593*** (-0.0034)
VAX65	-0.00418829*** (-0.0044)	-0.00621110*** (-0.0002)
GDP	-1.27667e-05*** (0.0000)	-1.44601e-05*** (0.0000)
DTP	0.0230867* (-0.0815)	0.0277396** (-0.0349)
RT	-0.108537* (-0.0877)	-0.105638* (-0.0671)
TOB		-0.0169265** (-0.0356)
OB		-0.00831111* (-0.0876)
Const.	-1.4823 (-0.2780)	-1.3682 (-0.2860)
sigma	0.131939*** (0.0000)	0.117690*** (0.0000)
Obs.	30	30

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

In Model 1 we first introduce variables that are related to country specific socio-economic and geographical characteristics: GDP, VAX65, DTP, TEMP and RT. The outcomes of the estimation show that GDP exerts a negative impact (strongly significant, at the 1% level) on public health sector efficiency. This finding can be interpreted through the Balassa (1964) - Samuelson (1964) effect according to which prices of non-tradable goods (i.e., most of government services such as health and education)[9] are higher in richer countries. This implies that the same quali-quantitative level of goods and services (output) requires a higher level of expenditure (input), determining a negative relationship between GDP and the efficiency scores. Furthermore, this represents an opposite finding with respect to the paper by Afonso e St. Aubyn (2011), that pins down a positive relationship between GDP and EFF. It is worth noticing, however, that their analysis is conducted in a pre-crisis time span (2003-2005). Thus, a further interpretation of our finding can be strictly linked to the down-turning phase of the economy (2007/2008 crisis).
Turning to the second socio-economic variable (VAX65), we find a further negative correlation (strongly significant, at the 1% level). This category of treatment captures the heterogeneous attitude of individuals towards preventive health care in each country. The negative sign, however, could be interpreted as the limited effectiveness, in some periods, of this form of elderly people vaccine on life-expectancy, and on overall EFF. As pointed out in Hawkes (2017), flu vaccination programmes for the over-65s can be ineffective, as in the UK in 2016. This could be in line with

[9] See Mano and Castillo (2015).

the recognition that: a) often the actual type of flu vaccines works less well with the elderly individuals (65+); b) costs could overwhelm benefits.

Vaccinations overall, however, are indeed a main component of preventive medicine. As for vaccine for children (DTP), by contrast, we find a positive correlation with the efficiency scores (significant at the 10% level). This finding can be interpreted as a positive balance between input (i.e., HE) and output (i.e., ISR), due to the higher effectiveness displaced by DTP (often mandatory by law) on the children's health status.

Geographical localization effects, picked by the variable TEMP, have a positive sign and are significant (at the level 5%): relative warmer countries exhibit a higher life expectancy.

As for the burden of administrative slowness (RT), we find the expected negative correlation (significant at the 10% level) with the efficiency scores. That is to say, the slowness of the bureaucracy in implementing public policies spreads in all sector of public intervention. The institutional framework efficiency, output being equal, enhances the expenditure (input) for the provision of health care services (see Cutler *et al*. 2012).

In Model 2, we furtherly add life-style factors as control variables. TOB and OB are both significant and with the expected sign. In terms of robustness of the previous estimation results, all regressors present the same sign and remain statistically significant.

In order to test the robustness of our results, table VIII reports the estimation results from the bootstrap procedure according to algorithm #1 from Simar and Wilson (2007), employing the same previous specifications (model 1 and 2) of the Tobit regression. Results are close to the Tobit ones, except for RT and OB, that are no longer significant. Even though with the same sign, the non-significant result of bureaucratic red tape could be due to the more limited binding effect of administrative procedures on the emergency provisions of health care treatments.

Table VIII: Bootstrap results. Dependent variable: FDH input-oriented efficiency scores

Simar & Wilson (2007) Bootstrap algorithm #1		
	Model 1 FDH	Model 2 FDH
TEMP	0.0205710** (-0.0126)	0.0223753*** (-0.00222)
VAX65	-0.00538710*** (-0.00713)	-0.00639011*** (-0.000647)
GDP	-1.02257e-05*** (-1.24E-04)	-1.09428e-05*** (-9.23E-06)
DTP	0.0156412 (-0.199)	0.0248569** (-0.0388)
RT	-0.0831456 (-0.167)	-0.0535543 (-0.359)
TOB		-0.0160742** (-0.0259)
OB		-0.000221677 (-0.962)
Const.	-0.766973 (-0.543)	-1.193989 (-0.318)
sigma	0.113659*** (-3.83E-11)	0.104321*** (-1.20E-11)
Obs.	24	24

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

It is important to note that our primary regressors, TEMP, VAX65, GDP, DTP and TOB, apart from maintaining the same sign and in some cases reinforcing the statistical significance of the Tobit regression, show very similar magnitude of the coefficients across the two alternative estimation techniques. This evidence reinforces the robustness of our findings.

5. Concluding remarks

In this paper, we analysed health sector efficiency in 30 countries by assessing output (HPI, based on infant survival rates; life-expectancy at birth; and hospital discharge rates) against input (per capita public health expenditure) and non-discretionary factors (per capita GDP, weather temperature, vaccine coverage, smoking habits and obesity, burden of administrative procedures). We have applied both the DEA/Tobit procedure and the Simar & Wilson Bootstrap algorithm #1. Results are very similar in these different estimation processes, which increases confidence in their reliability. Results from the first part of the analysis show that inefficiency is significantly high: on average, countries could use around 30-40% less resources to attain the same outcomes, if they were fully efficient. Results from the second part of the analysis show that per capita GDP, vaccine coverage and tobacco consumption are highly significant and strongly correlated to efficiency, in all the model specifications. In addition, we also control for geographical and institutional variables. While weather temperature is positively correlated to the efficiency health care scores through its positive effect on LE, bureaucratic red tape seems to play a more ambiguous role, probably due to the smaller relevance of administrative procedures when dealing with the provision of emergency health care treatments.

The findings obtained raise further policy implications. The enhancement of health sector efficiency cannot be obtained by a one-shot expenditure cut policy. It emerges that the complexity surrounding the multidimensional provision of health care services (i.e., preventive versus curative care, emergency versus ordinary care, elderly versus children) calls for a systematic and long-term approach. This is coherent with a paternalistic role of the State which is generally associated to a lower time preference rate with respect to individuals. The aim of enhancing care and clinical appropriateness should play a central role (see Mancuso *et al*. 2016).

Particularly, besides the lifestyle factors, the role of preventive care vaccine is relevant in terms of structural policy implications. The results for DTP suggest specific long-term policies in order enhance the awareness on infant immunization. This topic is relevant in the socio-economic debate in Europe. In Italy, for instance, the recent Law 119/2017 introduced a compulsory vaccination mix for the primary and secondary school enrolment. This policy measure has been central in the last national political elections, furtherly generating distorted information. Therefore, this requires a greater effort on knowledge diffusion of scientific medical research.

Findings obtained for VAX65 is counterintuitive. This is probably due to the interaction among different factors. Elderly individuals' immunization is designed to displace a limited effectiveness typically in the short term. The positive expected effect of the vaccine, however, is not granted. On the one hand, the flu vaccines work less well in the elderly because of weaker immune systems with respect to younger individuals and it is effective a limited number of flu strains. On the other hand, the target population is heterogenous with respect to the individuals' pathologies, requiring a greater attention to the appropriateness of this specific medical treatment. These considerations suggest that public policy should be addressed to increase the overall level of research and development investments to ensure an enhancement of the effectiveness of VAX65, improving the fine tuning with respect to flu strains. Moreover, public institutions could set down detailed guidelines to upgrade the appropriateness of this medical treatment for the elderly population.

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