ISSN 2443-8022 (online)

Efficiency of Public Expenditure in Education and Health

Giuseppe Canzonieri and Luigi Giamboni

DISCUSSION PAPER 217 | DECEMBER 2024

EUROPEAN ECONOMY

Economic and Financial Affairs

European Economy Discussion Papers are written by the staff of the European Commission's Directorate-General for Economic and Financial Affairs, or by experts working in association with them, to inform discussion on economic policy and to stimulate debate.

Authorised for publication by Géraldine Mahieu, Director for Investment, Growth and Structural Reforms.

This paper exists in English only and can be downloaded from
https://economy-finance.ec.europa.eu/ecfin-publications_en.

Luxembourg: Publications Office of the European Union, 2024

PDF ISBN 978-92-68-xxxxx-x ISSN 2443-8022 doi:10.2765/xxxxx KC-BD-2x-0xx-EN-N

European Commission

Directorate-General for Economic and Financial Affairs

Efficiency of Public Expenditure in Education and Health

Giuseppe Canzonieri, Luigi Giamboni

Abstract

This paper measures the efficiency of public spending in the education and health sectors using Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). It covers all EU Member States from 2000 to 2022. The model uses panel data and accounts for country-specific factors such as school systems, economic structure, socio-economic background, and health risks, treated as fixed effects. A common frontier approach, assuming equal access to production technologies across countries, is estimated with both methods. DEA also evaluates variable returns to scale and considers multi-output and multi-input analysis. The analysis shows that most countries operate near their efficiency frontiers for quantitative outcomes (tertiary education attainment rates and life expectancy at 65) while significant gaps seem to exist for qualitative targets (PISA scores and years of healthy life expectancy at 65). DEA analysis suggests the presence of decreasing returns to scale between public spending and outcomes in both domains. Malmquist index calculation points to technological shifts of the frontier to have a role in explaining inefficiency over time.

JEL Classification: H40, H51, H52, I11, I21.

Keywords: efficiency analysis, SFA, DEA, Malmquist index, investment in education, investment in health, government efficiency, government performance, quality of public finance.

Acknowledgements: The authors are grateful for valuable contributions and comments received by the Lisbon Methodology Working Group (LIME), Alessandra Cepparulo, Alessandro Turrini, Barbara Lipszyc, David Yim, Joana Elisa Maldonado, Kristine Van Herck, Luis Garcia Lombardero, Marco Montanari, Maya Matthews and Peter Voigt.

Contact: Giuseppe Canzonieri, giuseppe.canzonieri@ec.europa.eu, Luigi Giamboni luigi.giamboni@ec.europa.eu, European Commission, Directorate-General for Economic and Financial Affairs.

ABBREVIATIONS

DEA	Data Envelopment Analysis
DMU	Decision Making Unit
EA	Euro Area
EU	European Union
FTE	Full-time Equivalent
ML	Maximum Likelihood
OECD	Organisation for Economic Co-operation and Development
PPS	Purchasing Power Standard
SFA	Stochastic Frontier Analysis

CONTENTS

TABLES

GRAPHS

BOX

1. INTRODUCTION

Sound governance of public finances is essential for economic development. In particular, efficient public budget allocations to education and health are pivotal to enhance productivity and sustain economic growth, while also improving societal and individual well-being. Investing in these sectors can help bridging social inequalities, promoting inclusivity and stability and providing a strong foundation for long-term economic resilience and development. Demand for education is high, as productivity gains need a progressively more educated workforce. Similarly, demand for healthcare is also pushed up by population ageing and the rise in life expectancy accompanied by increasing chronic medical conditions. Meeting those demands while keeping public spending under control requires, among other things, efficient public spending.

Education and health represent a substantial share of government expenditure across all EU Member States. In 2019, EU countries allocated on average around 26% of their overall spending to these two items. An efficient allocation of funds in these sectors can improve wellbeing for all citizens and strengthen the growth of the economy.

In education, efficient use of public resources helps to expand the access to quality education, and to improve teaching standards, school infrastructure, and learning materials, leading to better academic outcomes. Consequently, the efficient use of funds improves the quality of schooling and skills development, which contributes to individual well-being and equips the workforce with the knowledge needed for higher productivity and innovation capacity. Furthermore, better qualifications endow the workforce with higher capacity to adapt to a faster changing environment, thus making people more resilient to the risk of becoming unemployed.

In health, efficient allocation of resources ensures better healthcare access and outcomes, reducing disease burden and healthcare costs. This leads to better health outcomes, increased well-being in the population, and reduced morbidity and mortality rates. Beyond enhancing individual well-being, improved health outcomes boost workforce productivity by reducing absenteeism, increasing efficiency, and promoting greater economic participation. Ultimately, the efficient use of public funds in education and health builds a strong foundation for long-term economic resilience and development.

This paper assesses the efficiency of public expenditure in education and health using Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). It evaluates the relative efficiency with which inputs are turned into outputs (i.e. "production efficiency") by comparing the outcome of each country with the outcome of the best performing country in the sample. Hence, efficiency measured by the country's distance to the estimated efficient production – the production frontier. For both policy areas, different outcome variables are considered in order to cater for their quantitative and qualitative dimensions. All EU Member States are covered over a period that, depending on the variables included in the analysis, extends to the years 2000 – 2022.

Two main issues may complicate the analysis. First is the shock related to the COVID-19 pandemic, which heavily affected both sectors under study. In the education sector, the pandemic resulted in prolonged school closures and distance learning which is likely to have affected educational outcomes, especially in primary and secondary education. The health sector was even more heavily affected, with the pandemic causing both a sharp increase in public health spending and a drastic drop in life expectancy. The second issue, which is also in part linked to the first one, is a potential endogeneity in the estimations. This may occur due to factors like omitted variable bias – from unobserved (country-specific) factors affecting our education and health outcomes and not being included as controls in the estimations – as well as reverse causality – with public spending reacting to the changes in outcomes caused by the pandemic.

The reference model allows for panel data and estimates efficiency while accounting for country-specific factors like school systems, economic structure, socio-economic background, and health risks, which are considered time-invariant and modelled as fixed effects (Greene, 2005a). This should at least partially address concerns about omitted variable bias. A common frontier approach, which implicitly assumes that countries have all access to the same production technologies, is also estimated with both methodologies. DEA is also exploited as it acknowledges the relevance of variable returns to scale, and provides a broader assessment of expenditure by allowing for multi-output and multi-input evaluations. Since DEA is based on cross-sectional data, the time dimension is reconsidered by calculating a Malmquist index. Both methods consider alternative specifications that incorporate additional control variables like private health expenditure and parental education levels. All estimations use lagged input variables to avoid potential issues with reverse causality.

The SFA results indicate that, over the sample period, most countries have improved their efficiency in achieving quantitative outcomes. Specifically, they are now very close to the efficiency frontier in terms of tertiary education attainment rates and life expectancy at age 65. In contrast, efficiency has declined in areas related to the quality of education and health, as measured by PISA scores and the number of healthy life years at age 65. Significant gaps remain in these domains relative to the estimated frontier. The DEA analysis corroborates the SFA findings and highlights decreasing returns to scale between public spending and outcomes in both areas. Additionally, the Malmquist index suggests that shifts in the technological frontier have contributed to the observed inefficiencies over time.

The paper is structured as follows. Section 2 introduces the concept of efficiency estimation and provides a brief overview of the two methods used - Stochastic Frontier Analysis and Data Envelopment Analysis – as well as a concise, non-exhaustive summary of their recent applications in the literature. Section 3 outlines the data and methodology, while Section 4 presents the results. Section 5 provides some concluding remarks.

2. ESTIMATING EFFICIENCY

Measuring the efficiency of public expenditure is a complex task. First, it is controversial whether the concept of a production function may be applied to the provision of public services such as education and health, and which functional form such a production function would have. Second, identifying appropriate input and output variables for assessing public spending efficiency is also challenging. Often, multiple inputs and multiple outputs may be relevant. Inputs can be both monetary – such as per capita expenditure on education – or non-monetary – like the student-to-teacher ratio. Similarly, outputs can capture the dimension of quantity (e.g., the percentage of population with tertiary education) or quality (e.g., PISA scores). The following subsections provide a brief overview of the key principles and methods used in SFA and DEA. For a detailed overview, refer for example to Coelli et al. (2005).

2.1. STOCHASTIC FRONTIER ANALYSIS

SFA methodology dates back to the early work by Aigner et al. (1977) and Meeusen & van den Broeck (1977). Their contribution to frontier analysis consisted in the introduction of a stochastic inefficiency component to the estimation of the production function, in the following form:

$$\ln y_i = f(x_i, \beta) + v_i - u_i \qquad (1)$$

where the subscript $i = 1, \dots, N$ indicates the Decision Making Units (DMUs) in the sample, i.e. countries in the present study. The random error term $v_i \gtreqless 0$ reflects the fact that the frontier is stochastic, being affected by favourable or unfavourable external events (statistical noise) and captures measurement error. The term $u_i \geq 0$ captures the DMU's inefficiency, as it reflects the notion that each DMU's output must lie on or below its frontier $[\ln y_i = f(x_i, \beta) + v_i]$ and thus represents the influence of factors that are under the DMU's control or, in other words, the DMU's inefficiency.

Common assumptions for this model are that the v_i are distributed independently from the u_i and that both errors are uncorrelated with the explanatory variable x_i. As the ordinary least squares (OLS) estimator of the intercept would be biased downwards, Aigner et al. (1977) proposed to estimate the model via maximum likelihood (ML), under the following assumptions:

$$v_i \sim iid\ N(0, \sigma_v^2) \qquad (2)$$

$$u_i \sim iid\ N^{+}(0, \sigma_u^2) \qquad (3).$$

A panel version of the model in equation (1), assuming a Cobb-Douglas production function with only one input, can be written as:

$$\ln y_{it} = \beta_0 + \beta_1 \ln x_{it} + v_{it} - u_{it} \qquad (4)$$

where the subscript $t = 1, \dots, T$ denotes the time dimension. Moving from a cross-sectional to a panel data model opens additional possibilities with regards to the modelling of the inefficiency term u_{it}:

1. A first and simple way is to model the inefficiency term as *time-invariant*, in other words setting $u_{it} = u_i$ for $t = 1, \dots, T$. Here the u_i is treated either as a fixed parameter (*fixed effects model*) or as a random variable (*random effects model*). However, assuming time-invariant inefficiencies may be an over restrictive and unrealistic assumption. For example, inefficient education systems may be expected to improve their efficiency over time.
2. A less restrictive way is to allow u_{it} to vary as a function of time:

   $$u_{it} = f(t) \cdot u_i \qquad (5).$$

   For example, Battese & Coelli (1992) model $f(t)$ as:

   $$f(t) = \exp\left[\eta(t - T)\right] \qquad (6)$$

   where η is an unknown parameter to be estimated. They propose to estimate their model in a random effects framework using maximum likelihood.
3. The common feature of the model above is that of assuming a single intercept for all countries. This can generate a mis-specification bias in the presence of time-invariant unobservable factors that might affect the output even though not relevant in the production process. Greene (2005a) addressed this issue by allowing for a country-specific intercept and a time-varying Normal-Half Normal model.[1]

   $$\ln y_{it} = \beta_{\mathrm{i}} + \beta_1 \ln x_{it} + v_{it} - u_{it} \qquad (7).$$

[1] The estimation of the so called True Fixed Effect model by Greene (2005a) requires addressing two issues related to the estimation of nonlinear panel-data models. The first is the large dimension of the parameter space. Nevertheless, Greene (2005a, b) showed that a maximum-likelihood dummy variable (MLDV) approach is computationally feasible also in the presence of a large number of nuisance parameters β_{i} (N > 1000). The second, the so-called incidental parameters problem, is an inferential issue that arises when the number of units is relatively large compared with the length of the panel. In these cases, the unit-specific intercepts are inconsistently estimated as $N \rightarrow \infty$ with fixed T. As this inconsistency contaminates the variance parameters, which represent the key ingredients in the postestimation of inefficiencies, the MLDV approach appears to be appropriate only when the length of the panel is large enough (T ≥ 10).

Box 2.1 **BENEFITS AND LIMITATIONS OF EFFICIENCY FRONTIER ESTIMATION IN PUBLIC ADMINISTRATION**

Efficiency frontier estimation is a powerful tool for assessing the efficiency and effectiveness of public expenditure. It helps to evaluate a government's allocation and utilisation of public funds in order to deliver services and achieve targeted outcomes. The application of this technique to public administration, and public expenditure in particular, has both advantages and limitations. The following are some of the benefits of estimating efficiency frontiers:

Identifying resource misallocation and providing a framework for benchmarking efficiency across Decision Making Units (DMUs). Efficiency frontier analysis helps to identify the DMUs (e.g. programs, regions, agencies, schools etc.) characterised by a relatively inefficient use of public expenditure and that consume a disproportionate amount of resources. The comparison of different DMUs allows the government to benchmark performances and to promote best practices and knowledge sharing.

Promoting accountability and fiscal discipline. The availability of objective, data-driven insights helps to hold public officials accountable for how taxpayer money is spent. This fosters transparency and reinforces trust in government financial management. At the same time, the identification of areas where expenditure can be reduced without sacrificing the quality or quantity of public services, leads to more cost-effective policies and promotes fiscal discipline.

Adaptability to different sectors. The approach can be applied to many public services, such as healthcare, education, or infrastructure. It offers flexibility in analysing sectors with different types of inputs and outputs/outcomes, enabling a broad assessment of public expenditure.

At the same time, there are a few limitations:

Homogeneity of DMUs. DMUs, e.g. countries, areas, government agencies, etc, are assumed to be homogeneous and with same access to production technologies, which may be a strong assumption.

Data quality and availability. Accurate and comprehensive data on public expenditure and outcomes are crucial for estimating efficiency frontiers. In many cases, data may be incomplete, unreliable, or not uniformly collected across regions or agencies, which can lead to flawed or biased results.

Difficulty in defining inputs and outputs. Clearly defining what constitutes inputs (e.g., financial resources, labour, infrastructure) and outputs (e.g., quality of healthcare, educational attainment) can be complicated. This is particularly challenging for services with intangible or long-term benefits. Inputs might be indivisible or not fully under control of the single DMU. Outputs are rarely attributed a market price. Moreover, public sector outcomes are often multi-dimensional and involve social, economic, and environmental factors.

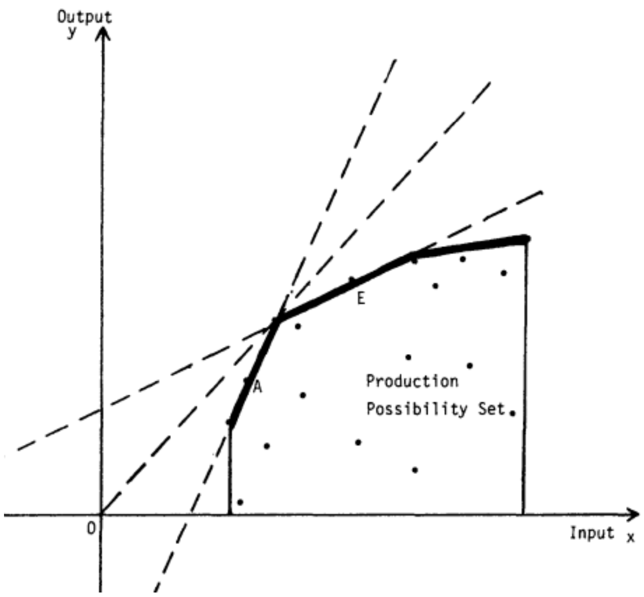
Other social goals. Public expenditure often aims to achieve social equity and welfare goals that may not be fully captured by efficiency frontier methods. Universal service obligation or programs targeted at disadvantaged groups are essential for promoting inclusiveness, fairness and social justice but often inefficient and non-quantifiable.

External influences. External factors beyond government control, such as economic conditions and demographics, might affect social outcomes and might distort efficiency frontier estimates, complicating the assessment of expenditure efficiency.

2.2. DATA ENVELOPMENT ANALYSIS

Farrell (1957) was the first to introduce the idea of frontier estimation by the construction of a piece-wise linear frontier that envelops the data as closely as possible (see Graph 2.1). He introduced the notion that the efficiency of a firm consists of two parts: technical efficiency, or the ability to maximise output for a given set of inputs, and allocative efficiency, referring to the use of inputs in optimal proportions, given their prices and technology.

Graph 2.1. **Construction of efficiency frontiers in DEA**



Source: Banker et al. (1984).

Data Envelopment Analysis (DEA) refers to the measurement of technical efficiency, although the term was introduced later by Charnes et al. (1978). They proposed to measure the efficiency of any DMU as the maximum of the ratio of weighted outputs to weighted inputs, subject to the ratio being less than or equal to unity. In other words, DEA solves the following maximisation problem:

$$\max h_0 = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}} \qquad (8)$$

subject to:

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1\,; \qquad j = 1, \dots, n, \qquad (9)$$

$$u_r, v_i \geq 0\,; \qquad r = 1, \dots, s\,; \qquad i = 1, \dots, m. \qquad (10)$$

where the y_{rj} and x_{ij} are the known outputs and inputs of the jth DMU and the u_r, v_i are the unknown variable weights representing the solution to the problem. This problem can be solved by linear programming to obtain estimates of DEA efficiency scores. The generated efficiency scores indicate the relative performance of each DMU compared to a reference DMU (i.e. the best performer in the sample).

The fact that the estimated efficiency frontier with DEA can be piece-wise linear allows for variable returns to scale. The case depicted in Graph refers to a typical case of decreasing returns to scale efficiency frontier: by raising inputs it might not be possible to obtain an increase in output in the same proportion, despite adopting the most efficient technologies.

Although DEA is a purely cross-sectional method, it is possible to extend its reach to the time dimension with the use of the Malmquist index (Caves, Christensen, & Diewert, 1982). This consists in calculating DEA efficiency frontiers and efficiency scores at two points in time (*t* and *t+z*) and the distance between the two frontiers. The overall change in efficiency is then given by the product of pure technical efficiency change (PTEC – a DMU getting closer to the frontier) and technological change (TC – a shift of the frontier):

$$MI_{t,t+z} = PTEC \times TC = \frac{D_{t+z}^{t+z}}{D_t^t} \sqrt{\frac{D_{t+z}^{t}}{D_{t+z}^{t+z}} \frac{D_t^t}{D_t^{t+z}}} \qquad (11)$$

where D is the distance of each DMU from the frontiers, the subscripts refer to the time where inputs and outputs are measured and the superscripts to the time where the frontier is set.

2.3. RECENT APPLICATIONS OF SFA AND DEA TO EFFICIENCY OF PUBLIC SPENDING

This section describes some examples of studies which analyse the efficiency of public expenditure by applying SFA and DEA methods. Afonso & St. Aubyn (2005, 2006) study the efficiency of spending on education using DEA with non-monetary inputs (teachers per student, time spent at school) and PISA results as output variable. They also employ a two-stage approach, using both Tobit regressions and bootstrap methods in the second stage, to analyse the impact of exogenous factors (for example socio-economic background like parental educational attainment) on the estimated DEA efficiency scores. By exploiting a panel of OECD countries, they revealed that efficiency varies across countries, regions and institutions. Finland and Korea were able to achieve high educational standards with relatively efficient use of public funds and stand as benchmark for other countries. They also highlighted that external factors such as socio-economic conditions, demographic differences and political stability strongly affect the efficiency of education spending. In a similar fashion, Jayasuriya and Wodon (2003) underlined the importance of the institutional frameworks and of policy decisions. Similarly, Afonso and St Aubyn (2011) investigated the geographical (and cross-system) variation of health spending efficiency and the impact of environmental and institutional factors. Countries with better governance structure, effective decentralisation and strong accountability mechanisms tend to be more efficient in their education and health expenditure.

Several papers have compared the efficiency of public versus private spending in the two domains, including Stevens (2005), Serrano-Cinca et al. (2005) and Amado and Dyson (2008). The findings are mixed, with some studies suggesting that private spending tends to be more efficient but the differences often depend on context and region considered. Nonetheless, there is also evidence that public expenditure deals with broader social goals such as universal access, which may require additional resources and can reduce estimated efficiency.

Returns to scale appear to play a significant role in both education and health expenditures. Findings suggest that there are often increasing returns to scale in education spending, implying that under-investment in certain areas/regions can lead to inefficiency (see Jayasuriya and Wodon, 2003). However, the effect diminishes at very high level of spending because of bureaucratic overhead costs and diminishing marginal returns. Similarly, by spreading fixed costs on a larger number of patients, large hospitals or health systems appear to operate better than smaller ones. In a paper on UK hospitals, Cooper et al. (2011) have shown that medium size ones appear to be the most efficient. Large ones are often facing coordination problems and bureaucratic inefficiencies while the small ones operate at a too small scale to properly handle fixed costs and they struggle with underutilisation of resources.

The European Commission (DG ECFIN) has also made extensive use of efficiency frontier methodologies. Medeiros & Schwierz (2015) analyse the efficiency of health care systems in the EU by using DEA (and SFA as an additional check). Their analysis includes 7 different outcome variables, including (healthy) life expectancy at birth and at 65. The input variable is either monetary – health expenditure per capita (public and private), in PPP – or non-monetary – such as hospital beds and the number of physicians and nurses. Other control variables like alcohol consumption, smoking, income and education are added to account for environmental factors. The DEA is carried out in a one-stage procedure, both in an output- and input-oriented fashion, assuming variable returns to scale. Confidence intervals – corrected for small sample bias – are estimated using Simar and Wilson's (1998) bootstrap method. Finally, they use the DEA scores to produce Malmquist indexes, which allow measuring gains in productivity over time. Bias correction shows that some countries' scores can be highly uncertain (large confidence intervals). Moreover, some countries, particularly the low performers, have high sensitivity to changes in inputs. Overall, they find that moving to the efficiency frontier could increase life expectancy at birth by 1.8 years on average in the EU.

Box 2.2 **ADVANTAGES AND LIMITATIONS OF SFA AND DEA**

SFA is a parametric method that assumes a functional form for the technology and the production process to estimate a stochastic frontier. As such the methodology has some **advantages.** The incorporation of a composed error term allows for randomness in the data. Deviations from the efficient frontier are split into two components: inefficiency and statistical noise (e.g. random shocks and measurement errors). Hence, SFA is more appropriate in handling situations where performance might be affected by external factors that are beyond the control of the DMU. It permits statistical testing of the hypotheses on assumptions regarding the production function and the efficiency. Moreover, the approach is flexible enough to handle different functional forms and assumptions regarding inefficiency and allows to exploit both cross-sectional and time dimension of the data.

The major **limitations** are linked with the approach being parametric. As already underlined a functional form of the production or cost function needs to be specified and might be inaccurate. The production function is also assumed to be homogeneous across DMUs. Observations have to be independent and identically distributed. The assumption about the distribution of inefficiency and noise (i.e. inefficiency being non-negative) might not hold in practice. Finally, data and computational requirements might be heavy (compared to DEA) and it does not allow to assess multiple outputs.

DEA is a non-parametric method that constructs efficiency frontiers from observed data, assessing the relative efficiency by comparing each DMU with the most efficient ones. The main **strength** of DEA is that it does not require the specification of a functional form for the production or cost function, making the approach more flexible. The approach allows for variable returns to scale and adapts well to the inclusion of multiple inputs and outputs.

The absence of structural assumptions is also what drives a few of the **limitations**. The method does not distinguish between inefficiency and random noise. Hence, any deviation from the frontier is assumed to be inefficiency, which might be over-estimated. Being a non-parametric method, results are strongly dependent on the data. Indeed, the estimated efficiency scores might be biased in small samples (but bootstrapping methods can help to correct it) or because of sample selection and outliers. Finally, the method relies on cross-sectional data and no time dimension is taken into account in the estimation (although the Malmquist index can provide estimates of efficiency gains over time).

Canton et al. (2018) employ SFA to assess the quality of public spending on education in EU Member States. They measure efficiency by looking at three separate dimensions: 1) *quantity*, by using total public spending on all education levels as input and tertiary educational attainment as output; 2) *quality*, with public spending on compulsory schooling as input and PISA science scores as output; 3) *inclusion*, by using total public spending on all education levels and the rate of the 25-29 year-olds not in employment, education or training (NEETs). They cover all EU Member States from 2002 to 2015 using COFOG data for expenditure and a mix of Eurostat and OECD data for the output variables. Their analysis employs two types of regressions: a pooled regression, which assumes that education systems are transferrable across countries (a common EU frontier), as well as a country fixed effects regression, which considers national education systems as country specific. They find that although efficiency of public expenditure has increased over time in the sample, many countries still have room for improvement. In order to improve, they argue, a country-specific policy mix is needed.

Cepparulo & Moore (2020) study the effectiveness of public spending across several areas of public administration, including education and health, by making use of expenditure by COFOG categories as input (where private input matters, for example health, they also include private expenditure). To assess the overall performance of countries, they build a composite indicator made up of seven sub-indicators, including education and health. For example, the education sub-indicator is made of five output variables, including PISA scores and tertiary attainment. Their results are mixed. No Member State stands out as the most efficient in all spending areas. None is the worst performer in all of them either.

3. DATA EVIDENCE AND CROSS-COUNTRY COMPARISON

This section describes the data used in the quantitative analysis (see Section 4). It provides evidence on where EU Member States (MS) stand in the education and health sectors, both in comparison to other developed countries and relative to each other. It shows the relative importance of education and health expenditure compared to other public expenditure categories; it analyses the recent expenditure trends; and it assesses the position of EU countries with regards to tertiary educational attainments, the quality of education (here proxied by PISA average scores), life expectancy and years of healthy life expectancy both measured at the age of 65.

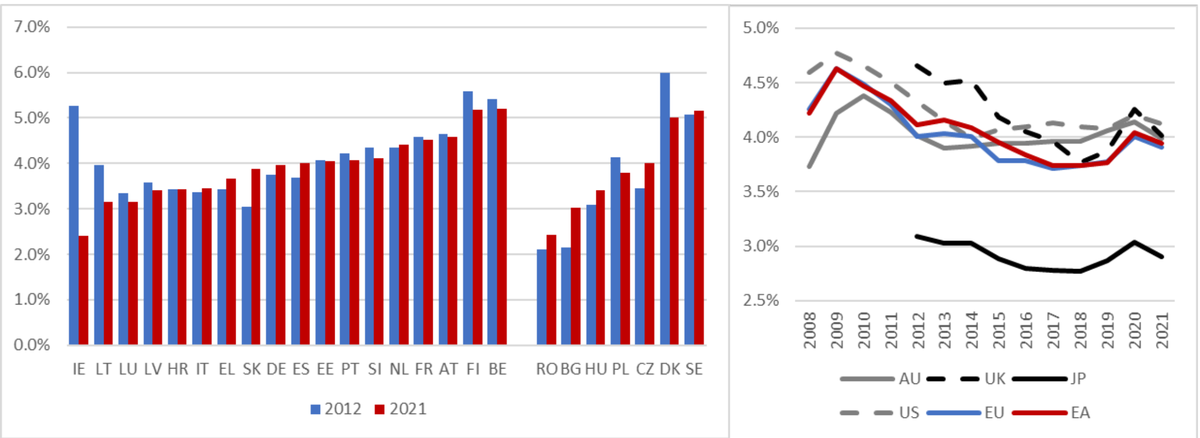
In 2021, on average, EU and EA countries allocate around 26 percent of their total public spending to education and health (COFOG data), with individual countries ranging from 18 (EL) to 33 percent (IE) (see Graph A.1 in the Annex). In comparison, the considered non-EU countries (AU, JP, UK and US)[2] allocate on average 32 percent of their public spending to education and health, with the US reaching a peak of more than 35 percent. Despite important support measures put in place during the pandemic increased the education and health spending, their share over total public expenditure remained almost unchanged compared to pre-pandemic period (given the generalised increase of public spending), Indeed, in 2019, EU and EA countries were already destinating 26 percent of their spending to education and health.

In both EU and EA countries, general government expenditure on education (as a percentage of GDP) has slightly decreased after peaking in 2009 because of GDP growth outpacing that of education spending. More recently, in between 2018 and 2020, expenditure over GDP has peaked again. In both cases the peak was largely a result of the GDP drop in the economic and financial crisis and during the COVID-19 pandemic. In 2021, with the GDP recovery the indicator seems to be back to the decreasing trend shown in the previous decade. This pattern is similar in other countries, with education expenditure in 2021 averaging around 4 percent of GDP across the countries shown in Graph 3.1 (JP the only exception at 3 percent). When total education expenditure is considered (hence including private spending), the gap

[2] These countries have been used only for comparison reasons in this descriptive section. Based on availability of COFOG data, estimate results presented in section 4 rely only on European countries (including CH, IS, NO, UK) and data available by Eurostat. This set of countries appears to be less problematic in terms of homogeneity assumption.

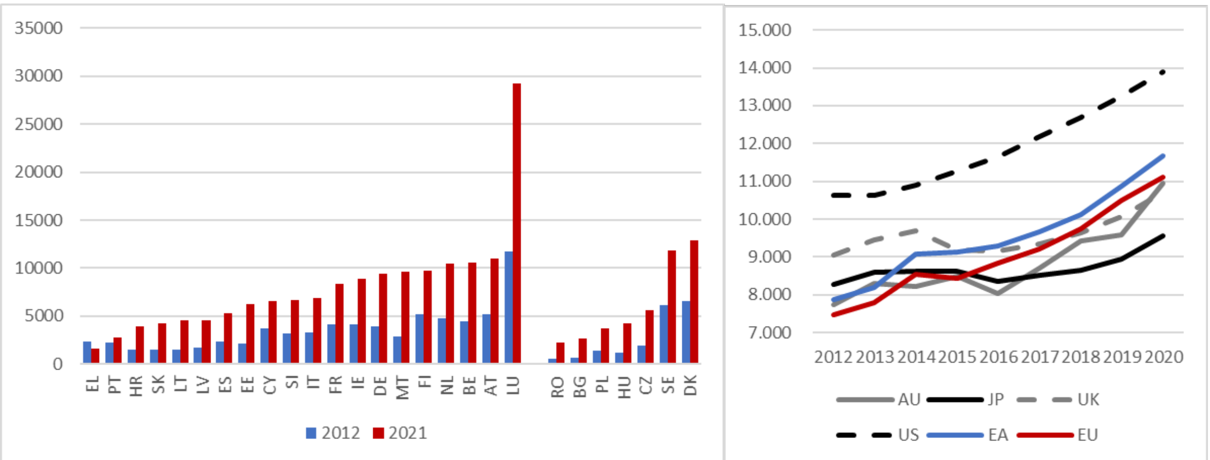
widens with AU, US and UK exceeding 6 percent, while EU and EA countries remain below 5 percent. Focusing on EU countries, government expenditure on education in 2020 ranges from less than 3 percent of GDP (IE) to over 5 percent (BE and FI). Compared to the beginning of the period (2012), government expenditure appears stable, with the exception of IE.[3]

Graph 3.1. **Public education expenditure as a share of GDP**



Source: UNESCO – OECD – Eurostat database on education. Data on EL refer to 2020.

Graph 3.2. **Public education expenditure per full-time equivalent student**



Source: UNESCO – OECD – Eurostat database on education for the international comparison. Data in $PPS.

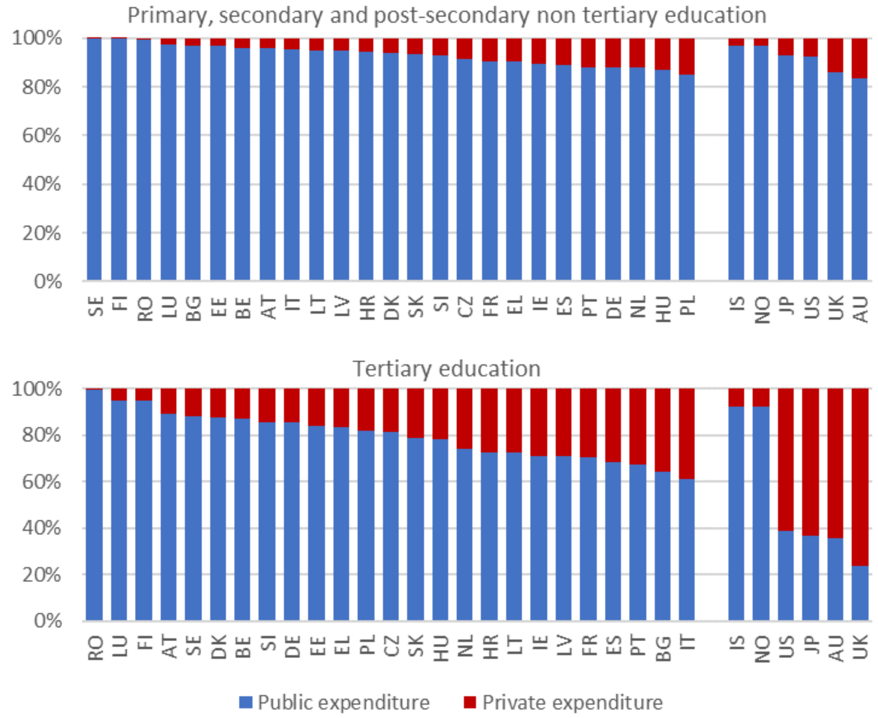
Public education expenditure per full-time equivalent (FTE) student has shown an upward trend over the last 10 years (Graph 3.2) given the increase in education spending and a relatively stable number of FTE students. In FTE terms, EU and EA countries generally spend slightly more than their peers, except for the US.

[3] It is to be underlined that Eurostat has stopped publishing figures on public expenditure on education as a percentage of GDP for IE and EE because of differences in the definition: (https://ec.europa.eu/eurostat/databrowser/view/educ_uoe_fine06/default/table?lang=en&category=educ.educ_uoe_fin.educ_uoe_fine). Moreover, GDP figures for IE suffer of the large discrepancy with GNP because of outflows of profits of foreign-owned multinationals.

Within the EU, LU stands out as a clear outlier.[4] With the exception of EL, all MSs have increased their spending per FTE student. However, spending across countries remains uneven, ranging from a minimum of 1600 $PPS (EL) to 12800 $PPS, in DK - nearly 8 times higher. The gap between the highest and the lowest spending countries has widened over the considered period, increasing from 6000 $PPS to 11000 $PPS.

Public expenditure is the primary source of funding for primary and secondary education in all countries, as well as for tertiary education within the EU (Graph 3.3). It finances from 85 percent to the total expenditure for these education levels. The funding is more balanced in tertiary education, with private sector funding (mainly households) playing a relatively larger role in some MS. Indeed, it exceeds 30 percent in IT, BG, PT and ES. In non-EU countries, the share of private funding is even more significant, surpassing 60 percent in the US, AU and JP and reaching 76 percent in the UK.[5]

Graph 3.3. **Distribution of public and private education expenditure by level of education - 2021**



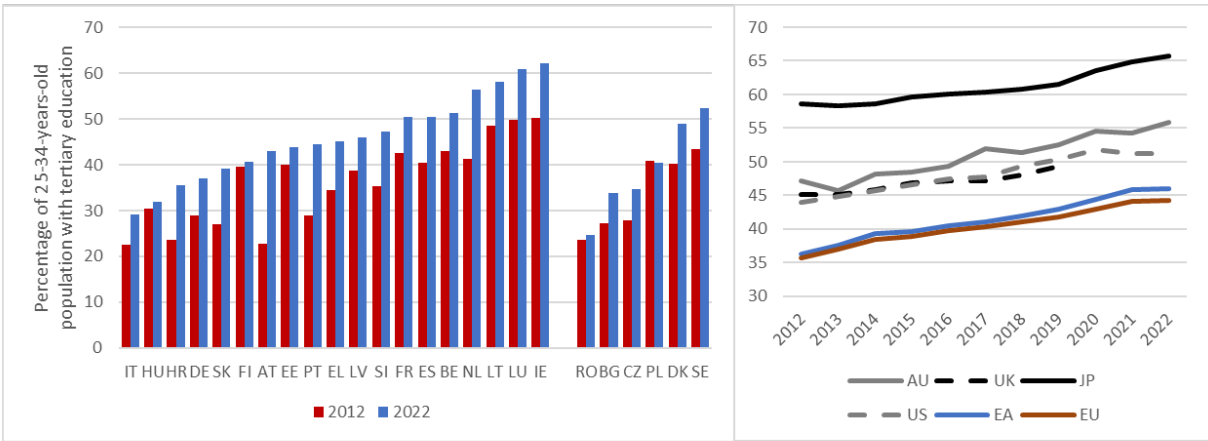
Source: UNESCO – OECD – Eurostat database on education. Data on EL refer to 2020.

[4] As explained in the methodology (https://ec.europa.eu/eurostat/statistics-explained/index.php?title=UNESCO_OECD_Eurostat_(UOE)_joint_data_collection_%E2%80%93_methodology#Introduction) indicators on enrolment statistics are combined with population statistics. The reference date for ages is the same (1st of January) but population data are based on residence whereas education data on enrolment. This might affect the data in some countries where the outflow of students is substantial (for example in Cyprus and Luxembourg), resulting in a low ratio of student to teaching staff. Moreover, in the case of Luxembourg high teachers' salaries at primary and secondary levels (see Indicator D3) are reflected in high levels of expenditure per student.

[5] In the efficiency analysis literature, referring to public education expenditure alone is considered a good approximation when focusing on EU countries. This assumption will be maintained in the next session, but comments will be made on the inclusion of private funding when needed.

Tertiary educational attainment rates have been rising in the last 10 years (Graph 3.4).[6] Despite a 10 pps increase in the percentage of 25-34-years-old population with tertiary education, EU and EA countries still lag behind their international peers by 5 to 20 pps. The top performers in Europe (IE, LU, LT, NL), perform better than AU, the UK and the US but remain 5 pps below JP. Within the EU, the picture is rather heterogeneous, with the percentage of tertiary educated people over the 25-34 age group ranging from 23 to 62 percent. Interestingly, the gap between the highest and the lowest attainment rates has widened in the considered time span, increasing from 27 to 39 pps.

Graph 3.4. **Tertiary educational attainment - 2012 to 2022**



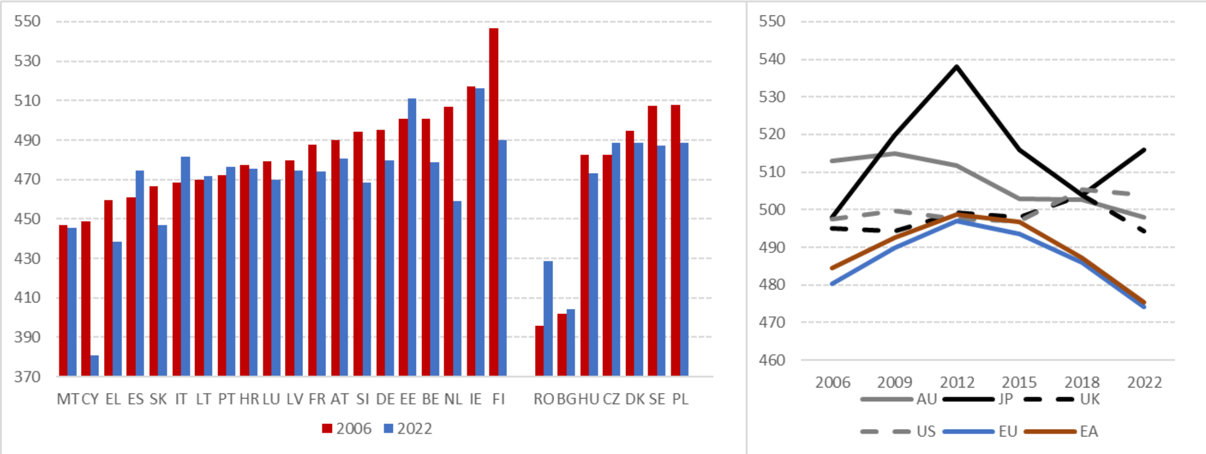
Source: UNESCO – OECD – Eurostat database on education.

The quality of education has been on a decreasing trend. In both EU and non-EU countries, average scores across the three dimensions of PISA - reading, science and mathematics - have been decreasing since the wave of 2012 (2009 for science), with the exception of reading scores in the UK and US (Graph 3.5, Graph 3.6 and Graph 3.7). All considered countries, except Japan, experienced a more pronounced decline during the COVID-19 pandemic. On average, EU and EA countries perform worse than their international peers, scoring at least 30 points lower in reading, 15 points lower in science and 20 points lower in math. EE and IE perform similarly to the best international peers.[7] The decline in students' performances is evident across most EU countries, with a few exceptions (notably IT, only country where students improved their scores between 2006 and 2022 in all three subject areas). As with the attainment rates, the results are quite heterogeneous, with a few "outliers" – CY, RO and BG – falling significantly below the EU average.

[6] Secondary educational attainment ratios show a similar evolution (not reported).

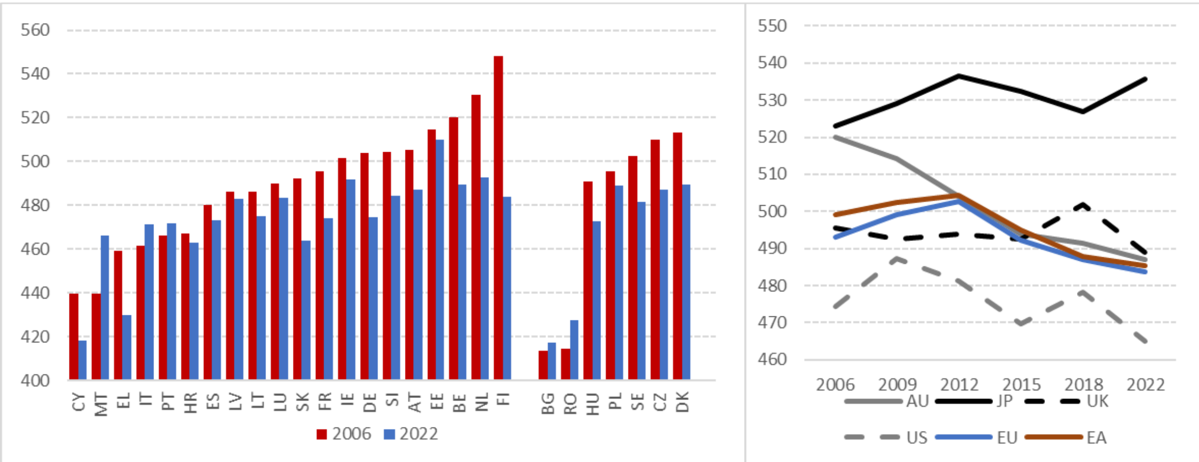
[7] Explaining the decreasing trends in PISA results will require further investigation as well as understanding the differences within EU and with respect to international peers. A few explanations in the literature refer to differences in the adoption of digital instruments, in early tracking of students, in competition among schools, in competence vs knowledge-based approach, etc. More recently, performances have been also influenced by school closing during the pandemic: notably JP managed to have really few days of school closing. Moreover, when looking more deeply at the distribution of the results, EU and EA countries seem to be less disperse, with better figures in under-achievements compare to a few peers, while countries like the US appear to be very polarised among extreme cases of excellence and of low performance.

Graph 3.5. **PISA reading scores**



Source: OECD. Note: LU did not participate in the 2022 edition of the PISA. The '2022' value shown above refers to 2018.

Graph 3.6. **PISA science scores**



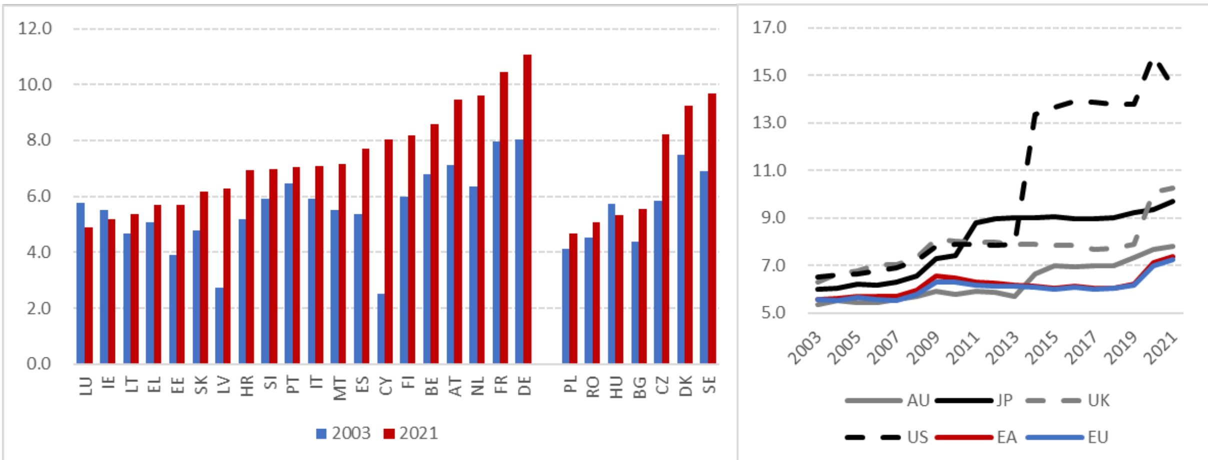
Source: OECD. Note: LU did not participate in the 2022 edition of the PISA. The '2022' value shown above refers to 2018.

Graph 3.7. **PISA math scores**

Source: OECD. Note: LU did not participate in the 2022 edition of the PISA. The '2022' value shown above refers to 2018.

Public expenditure on health as a share of GDP has remained stable in EU and EA countries, with a noticeable increase at the end of the considered period, corresponding to the COVID-19 pandemic (Graph 3.8). In contrast, international peers show some breaks in their expenditure series corresponding to the entry into force of some legislated reforms. The most notable case is the US, where the "Obama care" reform, legislated in 2010, entered into force in 2014. It is important to note that EU and EA countries allocate a smaller share of GDP to healthcare compared to peers. They spend several pps less than the UK and JP and less than half of what the US spends, which is around 15 percent of GDP. Among EU countries, DE, FR, NL and AT exhibit an expenditure share comparable to, or higher than, international peers, except for the US. The share of GDP allocated to healthcare has increased in nearly all EU countries over the period considered, with the exception of LU, IE and HU. In 2021, health expenditure distribution across EU countries was very heterogeneous, with those on the lower end spending around half of those at the higher end (4.7 against 11.1 percent of GDP).

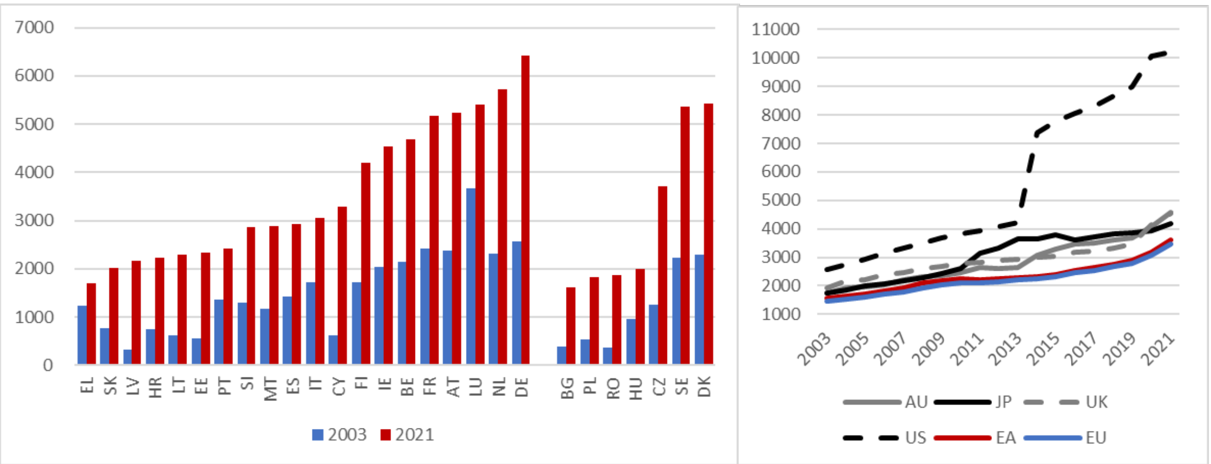
Graph 3.8. **Public expenditure on health as a share of GDP**



Source: OECD, data in PPS.

In per capita terms, public expenditure on health has been gradually increasing over time, with an acceleration during the COVID-19 pandemic (Graph 3.9). EU and EA countries spend less per capita than their international peers by approximately 1000 USD. Among EU countries, those with the highest expenditure per capita are also spending more than their international peers, except for the US. In 2021, despite all MS having increased expenditure per capita, the distribution of expenditure remains rather uneven. Countries at the lower end of the distribution spend, in Purchasing Power Standards (PPS) terms, just 1/6 of what countries at the highest end spend (1600 $PPS compared to 6400 $PPS).

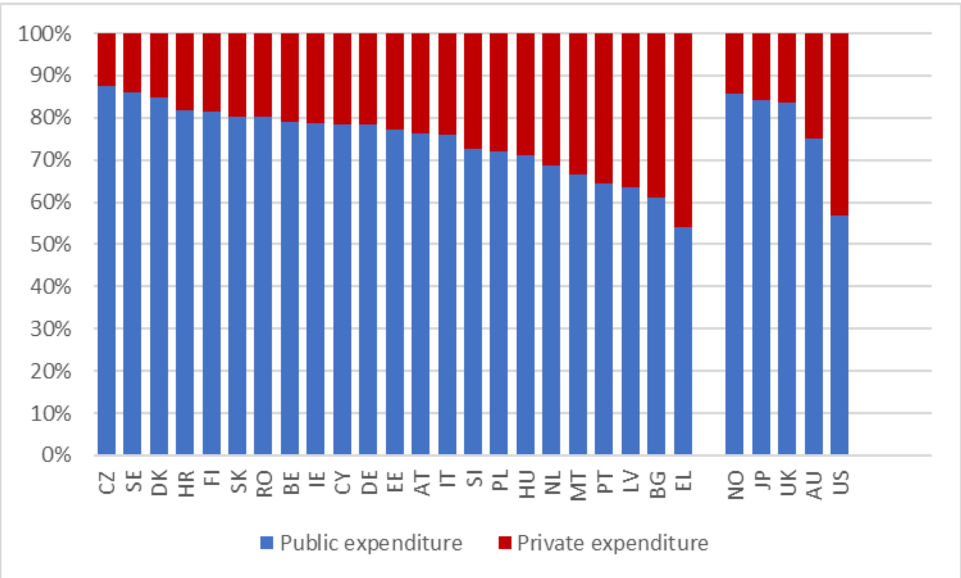
Graph 3.9. **Public expenditure on health per capita**



Source: OECD, data in PPS.

Public funding remains the main source of healthcare services (Graph 3.10). On average, public funding makes up 75 percent of the total health expenditure, ranging from 55 percent in EL to 87.5 percent in CZ. The share of private funding does not appear significantly different in non-EU countries. From NO (the lowest) to the US (the highest), it ranges from 15 to around 43 percent.

Graph 3.10. **Distribution of public and private health expenditure - 2020**

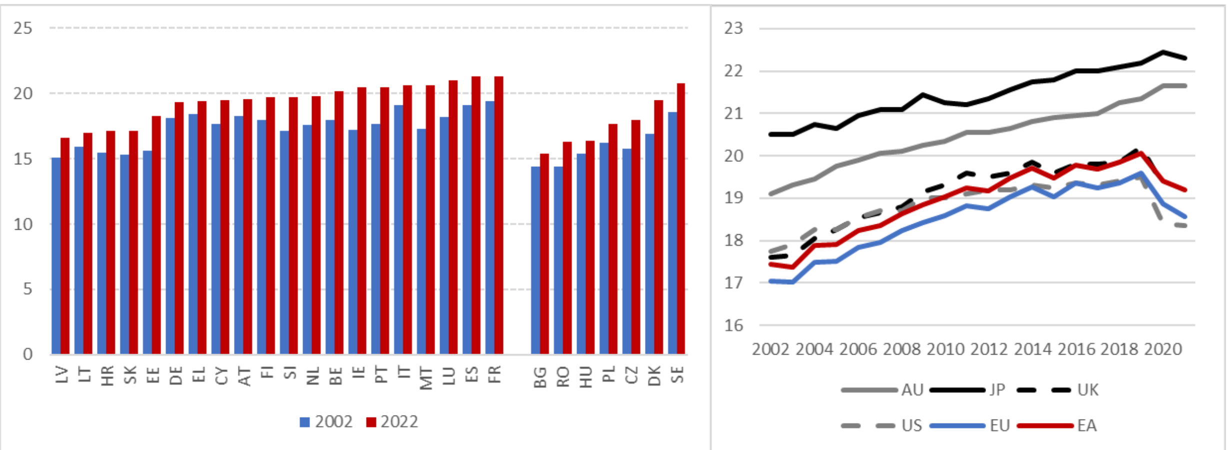


Source: World Bank.

The COVID-19 pandemic led to the first decline in life expectancy after decades of steady improvements (Graph 3.11). In the EA and EU countries, life expectancy at age 65 is in line with that of the US and the UK, at around 19 years (peak at 20 years in 2018), nearly three years lower than in JP and AU. JP and

AU are also besting the highest performers among the EU countries. Within the EU, life expectancy has improved over the past two decades (despite the recent decline), but significant differences remain. In 2022, a gap of up to five years persists between the lowest and the highest performing MS.[8] For instance, BG records 15 expected years and RO and HU 16 expected years compared to 21 expected years in FR, ES and SE.

Graph 3.11. **Life expectancy at 65 - 2002 to 2022**



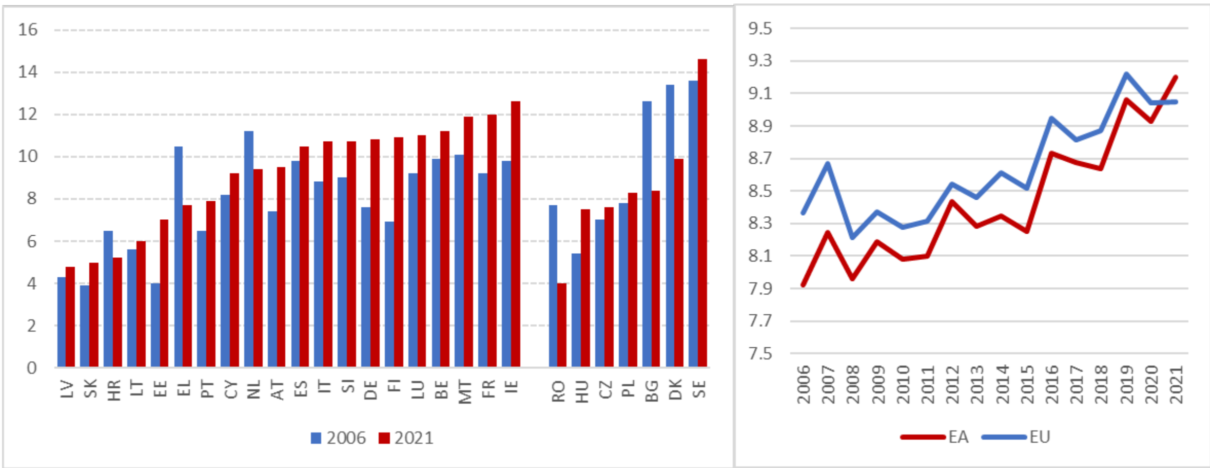
Source: Eurostat.

Between 2006 and 2021, EU and EA countries have gained, on average, one year of healthy life expectancy[9] (Graph 3.12). This improvement at aggregate level masks significant differences among MS. A few countries, such as RO, BG and DK, have not improved at all and have seen a reduction in healthy life expectancy by four years during this period. In seven MS, the variation – whether positive or negative – has been less than one year. FI has made notable progress, gaining four years, bringing its healthy life expectancy at 65 to 11 years. The highest value is recorded by SE (15 years), followed by IE (13 years).

[8] Recent publications find a gap of 8 years in life expectancy at birth between the highest and lowest performing Member States in 2022. Despite overall gains in life expectancy over time, the quality of these additional years remains a critical concern, as evidenced by more than 40% of EU citizens aged 65 and above living with at least two chronic conditions (OECD/European Commission (2024), Health at a Glance: Europe 2024: State of Health in the EU Cycle, OECD Publishing, Paris, https://doi.org/10.1787/b3704e14-en, Health at a Glance: Europe 2024 - European Commission).

[9] Healthy life years, also called disability-free life expectancy, are defined as the number of years spent free of long-term activity limitation. Healthy life years are calculated annually by Eurostat based on life table data and age-specific prevalence data on long-term activity limitations.

Graph 3.12. **Healthy life expectancy at 65 - 2006 to 2021**



Source: Eurostat.

4. RESULTS

4.1. ANALYTICAL STRATEGY

This section presents the results from the application of SFA and DEA analysis to both the education and health sectors. Below is a summary of the key methodological choices made for the analysis.

Sample:

The primary data source is Eurostat, while PISA scores are retrieved from the OECD database. The sample includes the 27 EU MS, and four non-EU countries - Iceland (IS), Switzerland (CH), Norway (NO) and the United Kingdom (UK) for comparison – to reduce the potential bias from excluding potentially more efficient European countries.[10] The chosen input and output variables are those commonly referred to in the literature.

Variables:

- *Education*: The analysis relies on tertiary educational attainment of 25–34-year-olds or PISA scores as output variables.[11] Attainment rates are a proxy for the *quantity* of (tertiary) education, while PISA scores are a proxy for the *quality* of (secondary) education. Public expenditure on (secondary or tertiary) education (COFOG) is the main input variable. In some

[10] Other regressions have been estimated including additional countries to those presented in the previous paragraph (e.g. the US, Japan, Australia, New Zealand, etc). To avoid any confusion through the use of a different dataset, their results are not shown and just mentioned when needed. The same reasoning applies to the inclusion of additional regressors like the average class size, statutory and actual wage of the teachers, body mass index data, tobacco consumption, etc.

[11] For SFA analysis, the variable considered is an unweighted average of the scores in the three components: reading, mathematics and science. For DEA analysis, the three scores are used as separate outputs.

model specifications, tertiary attainment of 45–54-year-olds is included as a proxy of parental educational attainment.[12]

- *Health:* The output variables are life expectancy and healthy life expectancy at age 65. The main input variable is public expenditure on health (COFOG). Some model specifications also include private health expenditure as an additional control.

Specifications:

- *Stochastic Frontier Analysis:* This method estimates efficiency while controlling for country-specific factors, such as school system, economic structure, socio-economic background and health risks. These factors change slowly over time, hence they are considered time-invariant and included as fixed effects. This will be the reference model, estimated with panel data along the lines suggested by Greene (2005a).[13] Nonetheless, efficiency across countries - assuming a common frontier - is also analysed by reporting on results on a panel data model with time-variant technology as in Battese and Coelli (1995).
- *Data Envelopment Analysis:* DEA assesses efficiency across countries using a common frontier approach. For each measure of output, a plot of the frontier will be based on the latest available data, while time evolution is measured by calculating the Malmquist index.[14] DEA accommodates multi-output and multi-input estimations, allowing for a more comprehensive evaluation of education and health expenditures.

For both methodologies, various alternative specifications (with and without fixed effects) are estimated incorporating additional regressors such as private health expenditure and parental education levels. The latter is significant in explaining quantity and quality of educational outcomes. In health, public systems funded by taxes are often supplemented by private insurance systems, where funds operate independently of the government. This complexity is accounted for by incorporating private health expenditure into some models.

Implementation:

The study performs an input-oriented SFA (input minimisation for given output level) where the production function is specified in a log-linearised form. DEA is also input-oriented and assumes variable returns to scale - which implies a piece-wise linear frontier of the type shown in Graph . Efficiency scores estimated with DEA are corrected for small sample bias using Simar & Wilson's (1998) bootstrapping technique, with 1000 iterations and 95% confidence intervals. Expenditure inputs are calculated as 5-years averages lagged by one period, reflecting that current outcomes depend on the cumulated expenditures over the previous years.[15] Allowing for lagged values of the average expenditure based on the previous 5 years is also a way to cater for reverse causality and assure that results are not biased because of endogeneity.[16] Health expenditure is measured *per capita*, while education expenditure is measured *per student*. In the case of DEA, all variables are normalised by dividing them by their cross-section mean as to bring them to a common scale. Finally, to show that results are not driven by the

[12] The age group 55-64 might also be considered. Here we kept the group 45-54 to have a proper comparison with Canton et al. (2018).

[13] The *sfpanel* Stata command has been used for performing the SFA regressions and calculating country specific frontiers.

[14] The *deaR* package for the R software was used to carry out DEA and calculate Malmquist indexes.

[15] Averages of different time spans have been considered, namely 3 to 10 years. The choice does not significantly affect the estimation results.

[16] It might be the case that underperformance in the dependent variable in a given year might induce, as a reaction, higher expenditure in the same year or in the subsequent ones (as it could be in the case of the COVID—19 pandemic). It is less probable that it influences the average expenditure of the 5 preceding years.

inclusion of the COVID-19 pandemic years, in the Annex we show empirical evidence based on a sample restricted to the pre-COVID-19 period.

4.2. EDUCATION

Two input-output pairs are analysed to reflect key educational dimensions: (1) public spending per student on tertiary education and tertiary educational attainment in the age group 25-34 (quantity); (2) public spending per student on secondary education and PISA average scores (quality). Empirical evidence from SFA shows that both quantity (tertiary educational attainment) and quality (PISA scores) outcomes are positively correlated with public expenditure per student.

Table 4.1. **Stochastic frontier analysis of education expenditure**

	Tertiary educational attainment - age group 25-34			PISA average score		
	ED1 Common frontier	ED2 (baseline) country specific frontier	ED3 country specific frontier	ED4 Common frontier	ED5 (baseline) country specific frontier	ED6 country specific frontier
Public tertiary education expenditure per student (1 lag 5 years average, log)	0.109***	0.344***	0.0658***			
	(7.59)	(9.88)	(4.89)			
Public secondary education expenditure per student (1 lag 5 years average, log)				0.0237***	0.367***	0.259***
				(7.71)	(183.15)	(5.76)
Share of the parents with tertiary education (log)			0.649***			0.540***
			(51.70)			(10.61)
Trend	0.0195***			-0.00331***		
	(11.53)			(-6.35)		
Constant	2.446***			6.113***		
	(17.66)			(215.93)		
Variance of inefficiencies (usigma)	-1.918***	-2.577***	-3.555***	-4.630***	-5.163***	-11.29*
	(-4.91)	(-42.29)	(-57.98)	(-9.24)	(-28.70)	(-2.40)
Variance of random error term (vsigma)	-4.243***	-13.59***	-10.85***	-7.451***	-7.317***	-4.213***
	(-17.84)	(-9.04)	(-7.09)	(-47.81)	(-19.44)	(-39.72)
Signal-to-noise ratio	1.800***	145.8***	83.606***	4.096***	2.935***	0.029**
Observations	572	572	572	395	395	394
Average number of years	18.5	18.5	18.5	12.7	12.7	12.7
Number of countries	31	31	31	31	31	31

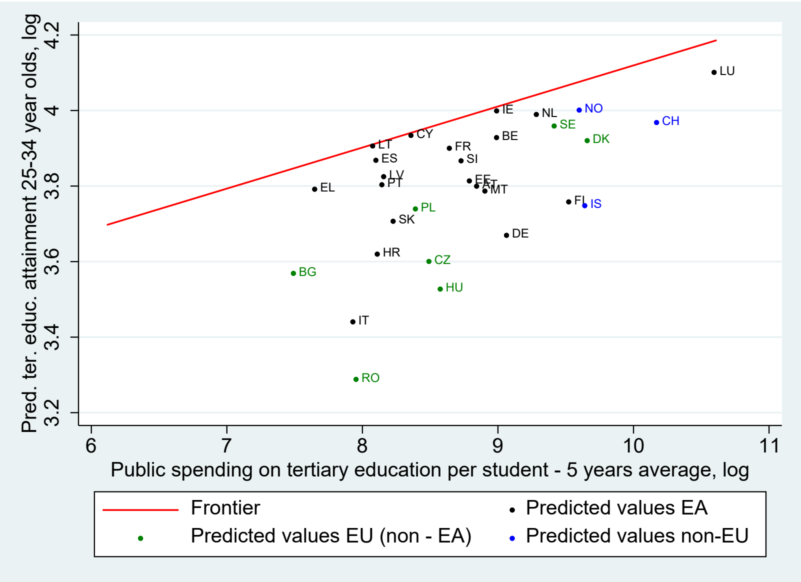
Note: Standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1. Significant standard deviations of the inefficiency terms (usigma) and significant signal to noise ratios indicate the existence of inefficiencies. All models are estimated using STATA command "sfpanel". Common frontier models (ED1 and ED4) estimated assuming a time variant technology specified as in Battese and Coelli (1995). Country specific frontier model (ED2, ED3, ED5 and ED6) estimated with a fixed effect parameter as in Greene (2005a).

4.2.1. Attainment rates

Public tertiary education expenditure is positively associated with the number of graduates. This effect comes on top of time-invariant factors captured by the fixed effects in our baseline (model ED2 in Table

4.1) or on top of modelling a time-variant common frontier (ED1).[17] The trend variable included in the common frontier model indicates that efficiency has increased over time. The estimated effect of expenditure is robust to the inclusion of additional regressors (ED3). However, the coefficient diminishes to close to zero when a proxy for the education of the parents is included among the regressors. This variable, which captures individuals' social and environmental background, emerged as the most influential factor in explaining the education outcome, alongside public expenditure (ED3).[18] The inclusion of a lagged value of the output variable (as in the case of this two age groups) could also capture factors like path dependency, educational infrastructure, past investment, etc.. Here, we aimed at having an additional control on top of what is captured by the country fixed effects and we reported on it to have a direct comparison with Canton et al. (2018). The correct interpretation of this additional regressor is left to future investigations.

Graph 4.1 **Tertiary educational attainment on tertiary education expenditure per student - 2022**



Note: Observations distance from the estimated frontier can be interpreted as how much more tertiary educational attainment could be achieved in a country with the same amount of average spending. Results distinguish between EA countries (black), EU countries not adopting the euro (green) and non-EU countries (blue). Frontier based on the common frontier model ED1 reported in Table 4.1.

Graph 4.1 shows the estimated log-linearised production frontier and the MS's distance from the common frontier. The shown production frontier is deterministic and derived from SFA model ED1

[17] Given that expenditure for FTE for LU appeared out of scale compared to other countries (see Graph 3.3), we performed some outlier detection technique including excluding LU from the regression. Results are not driven by LU or any other influential observations.

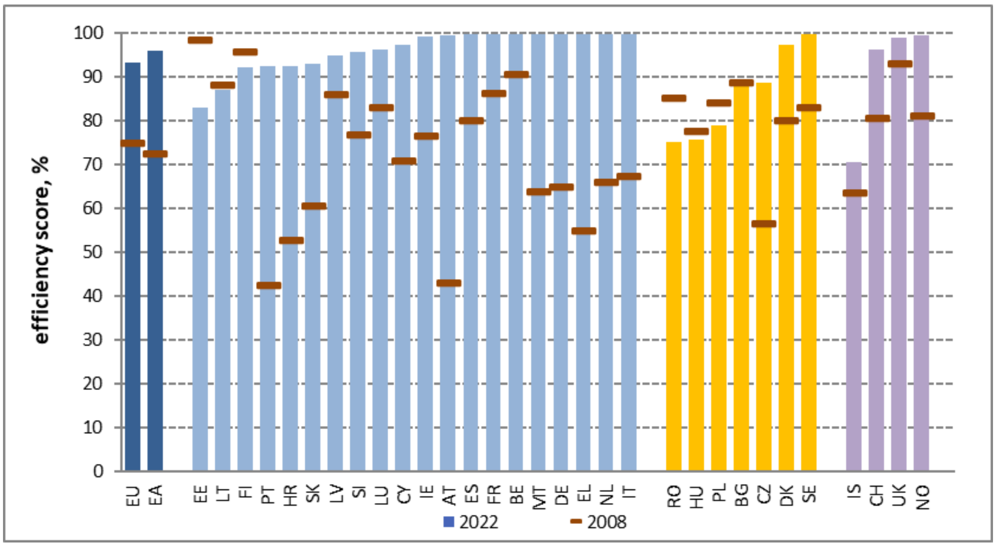
[18] The significance of public expenditure remained robust to the inclusion of many other regressors. Many controls on the administrative side have been tested. The student-teacher ratio resulted to be positively correlated and significant. The teacher salary (a proxy for teacher's productivity), the average class size, the institutional number of hours (per student and in level) and the private education expenditures (per student or as a share of GDP) do not have a significant impact. Private expenditure is becoming more relevant when the US, AU, JP and NZ are included in the sample. These countries are indeed characterised by a larger share of private expenditure on tertiary education (see section 2). Results have not been reported, as these are based on an alternative dataset not fully comparable with the baseline specification.

(common frontier, Table 4.1) by removing the stochastic error component (for 2022). The distance from the frontier can be interpreted as a measure of relative inefficiency with respect to the common technology frontier. EA countries (represented in black in the graph) perform relatively better than non-euro EU countries (green). Additionally, the non-EU countries (blue) included in the sample to address potential selection bias, also perform well in terms of tertiary attainment rates.

As previously highlighted, countries exhibit unique characteristics, and efficiency can be assessed within the context of their own country-specific frontiers. Graph 4.2 presents efficiency scores derived from the baseline model with fixed effects (ED2 – country specific frontier, Table 4.1). Fixed effects allow to control for time-invariant country-specific factors such as institutional frameworks, the role of various government tiers, and cultural nuances. These factors, given their gradual evolution, are considered stable in the short- and medium-term. As such, they are assumed to be time-invariant within the period covered by the dataset. However, as underlined by Canton et al. (2018), it is important to acknowledge that, if inefficiency is time-invariant, it might be captured by the fixed effects.

More importantly, the efficiency of public spending on education in EU MS has notably improved in recent years. On average, EU and EA countries have increased their efficiency by approximately 18 and 24 pps respectively over the analysed period. A few countries - namely AT, PT, EL and HR - have seen improvements exceeding 40 pps. Currently, when referring to tertiary educational attainment rates, nearly all EA countries are efficient with respect to their own country-specific frontier. Therefore, further enhancement would require the countries to push their country-specific frontiers outward by reforming their educational systems and/or adopting innovative teaching methodologies (technological shift). Some room for efficiency gains remains for EU countries that have not adopted the euro.

Graph 4.2. **Efficiency scores related to tertiary educational attainment and tertiary education expenditure per student**

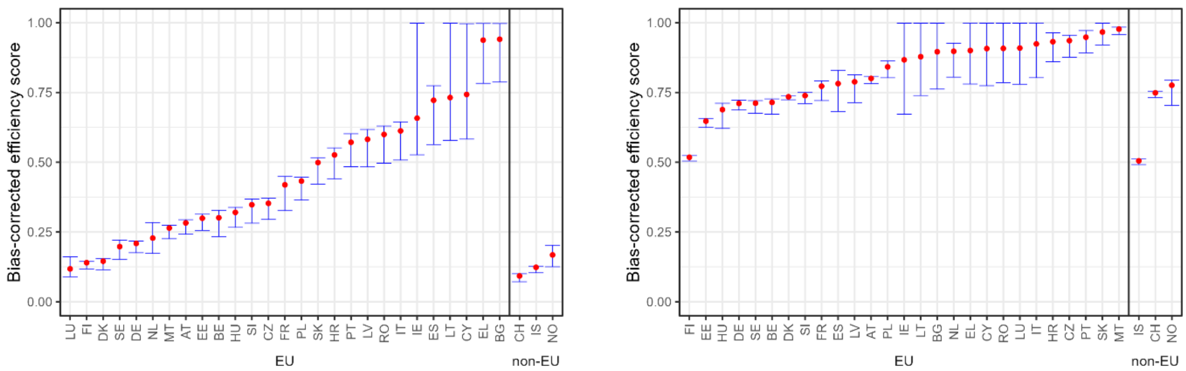


Note: EU and EA are based on unweighted averages as all the indicators involved in the estimation of the efficiency scores are measured per student. 2019 data for UK.

DEA is also used as a verification of the SFA results (Graph 4.3). The first DEA estimation (D.ED1) mimics SFA estimation ED1 from Table 4.1 but referring to the single cross-section for the year 2022. Hence, tertiary educational attainment of 25–34-year-olds in the year 2022 is used as output and the lagged 5-year average (2017-2021) of public expenditure per student on tertiary education as input. The second DEA estimation (D.ED2) includes tertiary educational attainment of 45–54-year-olds as an additional input.

Graph 4.3. **Bias-corrected DEA efficiency scores with tertiary attainment of 25–34-year-olds as output**

(D.ED1) (D.ED2)



Note: The output variable refers to the year 2022. The input variable in D.ED1 is the 5-year average (2017-2021) of public expenditure on tertiary education (COFOG). D.ED2 includes the 5-year average (2017-2021) of tertiary educational attainment of 45–54-year-olds as a second input. Blue error bars indicate 95% confidence intervals.

Results from DEA are broadly in line with those obtained from SFA, though there are some notable differences. In estimation D.ED1, countries such as EL, CY, LT, ES and IE stand out among the top performers, similarly to the findings from SFA model ED1 (compare Graph 4.3 with Graph 4.1, where the aforementioned countries are positioned close to the predicted common efficiency frontier).[19] However, these countries' scores also exhibit the largest confidence intervals. Moreover – and in contrast with SFA results – BG emerges as the most efficient, while LU is the least efficient. These partially contrasting results can be explained in light of two important methodological differences between SFA and DEA. First and foremost, the efficiency frontier estimated by DEA is non-linear because of the assumption of variable return to scale. This non-linearity enables DEA to better fit the observed data points and generates some differences in the estimated efficiencies of countries that are at the two tails of the expenditure distribution (where SFA assumption of constant return to scale becomes more problematic) Second, DEA is a cross-sectional method, and bases its results only on the most recent wave of data (2022 in the specific case), whereas SFA can take advantage of longer panel data.

When parental tertiary attainment is considered as an additional input - as in model D.ED2 - some notable differences appear for a few MS. In particular, LU moves closer to the top performers and MT comes out to be the best performer. At the same time, the gap between the highest and lowest efficiency scores narrows and some of the largest confidence intervals diminish compared to the single-input estimation in D.ED1.

Overall, the most efficient countries tend to be those that spend comparatively less on education. This is the case, for example, for CY, EL, BG, PT and SK (see Graph A.2 in the Annex). Conversely, countries with higher education spending, such as LU, DK and FI are estimated among the least efficient. This pattern may again be a consequence of the assumption of variable returns to scale in the DEA estimations, suggesting decreasing returns to investment in education. Several countries with lower spending appear to be close to the steep part of a piece-wise linear efficiency frontier (as the one depicted in Graph 2.1).

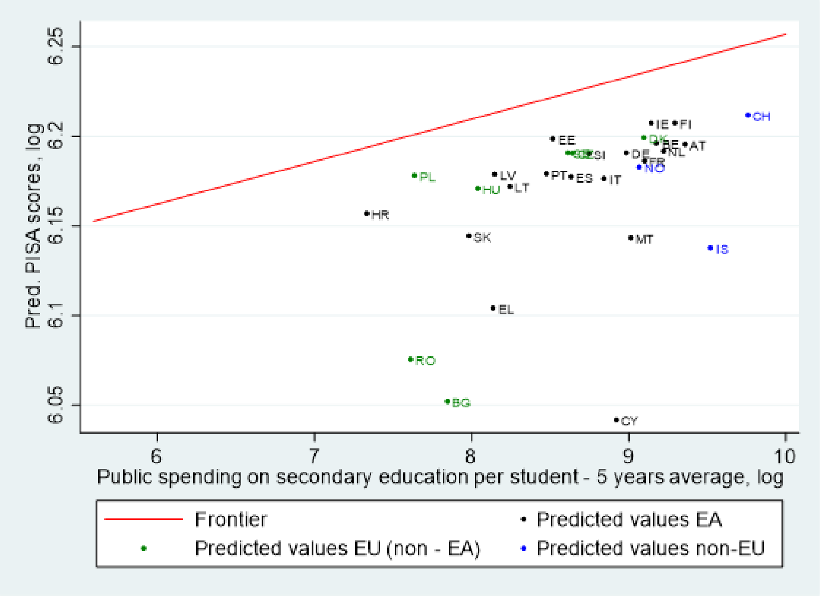
[19] To be kept in mind that any comparison between DEA and SFA should be made with respect to the common frontier models of SFA, since DEA does not take into account any country-specific effects.

Moreover, confidence intervals tend to be larger for countries that are closer to the frontier, especially for the single-input estimation.

4.2.2. PISA scores

In the subsequent analysis, PISA scores are used as output as a proxy for the quality of the education systems. As in the previous estimation, the measure of public expenditure - here expenditure per student on secondary education - is positively correlated with the outcome under both assumptions about the frontier – country specific and common (ED4-ED6 in Table 4.1). When adopting a common frontier approach (ED4), the coefficient for public expenditure, though positive, is nearly zero. Additionally, the trend variable indicates a decline in efficiency over time, coherently with the observed decrease in PISA scores discussed in the previous section.[20] The expenditure coefficient is larger in the baseline model (ED5), when assuming a country specific frontier. This suggests that national contexts may affect the efficiency of resource allocation. Once again, parental education emerges as a significant factor in explaining students' cognitive performance (ED6).

Graph 4.4. **PISA average scores on secondary education expenditure per student – 2022**



Note: Observations distance from the estimated frontier can be interpreted as how much more cognitive skills (as measured by PISA) could be achieved in a country with the same amount of average spending. Results distinguish between EA countries (black), EU countries not adopting the euro (green) and non-EU countries (blue). Frontier based on the common frontier model ED4 reported in Table 4.1.

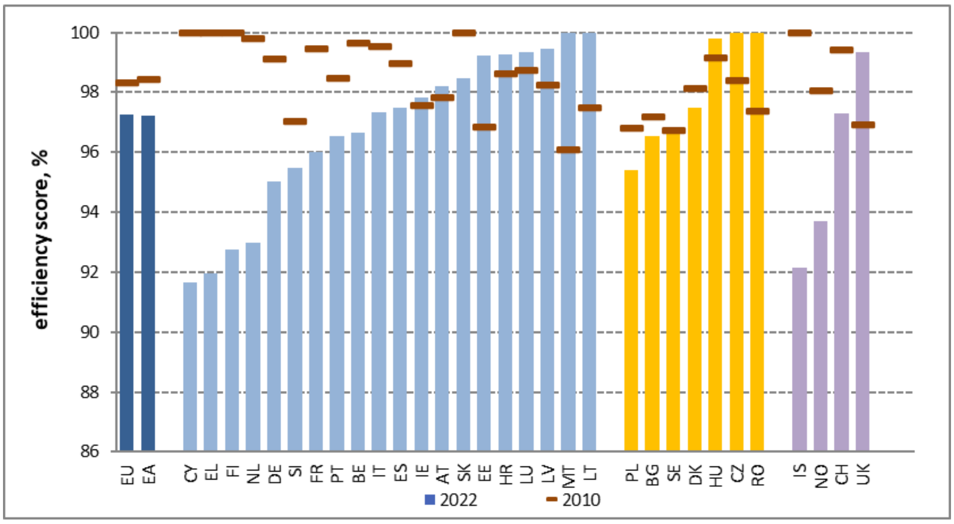
In 2022, corresponding to the last round of PISA tests, no country reaches the efficiency frontier (Graph 4.4). This implies that the frontier, as defined by model ED4 – common frontier in Table 4.1 - is based on earlier observations and efficiency has declined over time. This finding is again consistent with the evolution of the

[20] See European Commission (2023, 2024) on the relationship between public spending and education results and the recent note to the Eurogroup of 24-04-2024, https://www.consilium.europa.eu/media/mrwnj5qy/comm-note-ea-competitiveness-addressing-the-knowledge-gap.pdf.

PISA scores (declining) and expenditure (rather constant) presented in the previous section.[21] With a few notable exceptions, most countries remain at a similar distance from the common frontier.

Although the existence of a common trend is less clear compared to the attainment ratios' case, many countries exhibit a declining efficiency trend relative to their own specific frontier (as shown in Graph 4.5). At the aggregate level, both in EA and EU, the average reduction is modest and limited to around a percentage point. However, a few countries - notably CY, EL, FI and NL - have experienced more significant reductions, ranging from 6 to 9 pps. This declining trend is also observable in non-EU countries. The country specific frontiers are derived from model ED5 in Table 4.1.

Graph 4.5. **Efficiency scores related to PISA average score and secondary education expenditure per student**



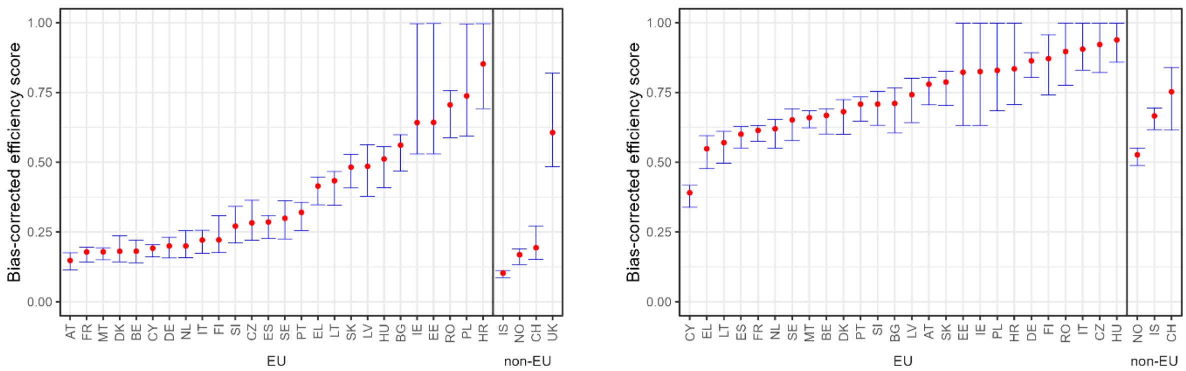
Note: 2012 data for CY, 2018 data for LU and 2020 data for UK. EU and EA are based on unweighted averages as all the indicators involved in the estimation of the efficiency scores are measured per student.

As done above for the *quantity* of education (attainment rates), we also apply DEA methodology to estimate the efficiency of public spending on the *quality of education* (average PISA scores) (Graph 4.6). Estimation D.ED3 utilises PISA scores from 2022 as output variable with the 5-year average (2017-2021) of public expenditure per student on secondary education as input variable. In estimation D.ED4, tertiary educational attainment of 45–54-year-olds individual is considered as a second input.

[21] When splitting the sample into two periods, it is evident that the positive coefficient is mainly driven by the evolution before 2018. If regressing on the last two waves of PISA, the coefficient is slightly negative but non significant (probably because of short T dimension).

Graph 4.6. **Bias-corrected DEA efficiency scores with PISA scores (math, reading, science) as output**

(D.ED3) (D.ED4)



Note: The output variable refers to the year 2022. The input variable in D.ED1 is the 5-year average (2017-2021) of public expenditure on secondary education (COFOG). D.ED2 includes the 5-year average (2017-2021) of tertiary educational attainment of 45–54-year-olds as a second input. Blue error bars indicate 95% confidence intervals.

The results from model D.ED3 largely mirror those from SFA with a common frontier (model ED4 from Table 4.1). PL and HR emerge as the most efficient MS, which is somewhat in line with the results from SFA ED4 (compare Graph 4.6 with Graph 4.4, with the same caveats on the methodological differences between SFA and DEA, as previously discussed). Once again, the three highest efficiency scores are obtained by the three lowest spenders on secondary education (see Graph A.3 in the Annex). Moreover, the confidence intervals are larger for many countries situated close to the frontier, such as HR, PL, EE, IE. As already observed with tertiary education attainment rates, including parental attainment as a second input significantly alters the results. IT, CZ and HU obtain the highest efficiency scores, while some of the largest confidence intervals are reduced.

4.2.3. Education overall (multi-output DEA)

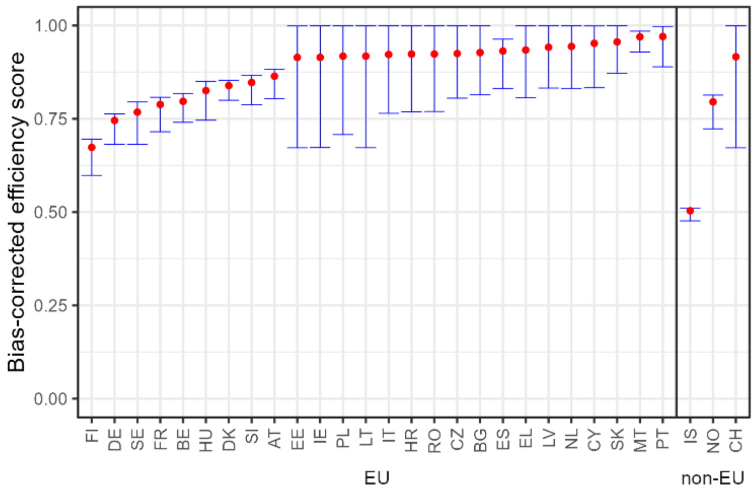
Estimation D.ED5 (Graph 4.7) exploits the ability of DEA to handle multiple outputs and multiple inputs. It does so by including all the output and input variables considered above, namely:

- Outputs:
  - Tertiary education attainment of 25–34-year-olds in 2022;
  - The three PISA scores (math, reading, science) in 2022.
- Inputs:
  - Public expenditure on secondary education, per student (5-year average 2017-2021);
  - Public expenditure on tertiary education, per student (5-year average 2017-2021);
  - Tertiary education attainment of 45–54-year-olds (5-year average 2017-2021).

The results obtained involve a high degree of uncertainty. Although PT, MT and SK obtain the highest efficiency scores, many countries obtain similar scores and with large confidence intervals.

Graph 4.7. **Bias-corrected efficiency scores from multi-output DEA (education)**

(D.ED5)



Note: The output variables are tertiary educational attainment of 25–34-year-olds and the PISA scores in math, reading and science in the year 2022. The input variables are the 5-year averages (2017-2021) of: i) public expenditure on secondary education (COFOG); ii) public expenditure on tertiary education (COFOG); iii) tertiary educational attainment of 45–54-year-olds. Blue error bars indicate 95% confidence intervals.

Table 4.2. **Malmquist indices of changes in efficiency of education spending 2006-2022**

DMU	MI	PTEC	TC	DMU	MI	PTEC	TC
AT	1.07	1.14	0.94	IT	1.09	1.01	0.55
BE	0.78	0.82	0.95	LT	0.63	1.00	0.56
BG	0.55	1.00	0.55	LV	0.60	1.00	1.00
CZ	1.00	1.00	1.00	NL	1.23	1.07	1.11
DE	1.41	1.26	1.11	PL	0.70	1.00	0.65
DK	0.98	1.10	0.89	PT	0.81	1.00	0.82
EE	0.65	1.00	0.65	RO	0.70	1.00	0.83
EL	1.29	1.57	0.82	SE	0.88	0.80	1.22
ES	0.80	0.96	0.83	SI	0.81	0.87	0.78
FI	0.85	0.70	1.22	SK	0.72	1.00	0.99
FR	0.63	0.81	0.78	CH	0.56	1.00	0.56
HR	1.36	1.38	0.99	IS	0.85	0.87	0.95
HU	0.60	0.85	0.71	NO	0.97	1.16	0.89
IE	0.67	1.00	0.94				

Note: MI = Malmquist index; PTEC = Pure technical efficiency change; TC = Technological change. MI=PTEC·TC. Values above (below) one indicate an increase (decrease) in efficiency. The input and output variables are the same as in estimation D.ED5 (Graph 4.7).

Finally, the Malmquist Index provides an estimate of changes in efficiency between 2006 and 2022. Table 4.2 shows the results obtained with a multi-input and multi-output model analogous to the model in estimation D.ED5, with the overall Malmquist Index also being decomposed into pure technical efficiency change and technological change. Only 7 EU countries seem to have improved their efficiency (MI value above 1), with the largest improvement recorded for DE, HR and EL. All other MS have experienced a deterioration, with the lowest scores belonging to BG, CH, HU and LV. In particular, the technological change component being below one for most countries in the sample seems to point to an adverse shift in the technological frontier.[22]

4.3. HEALTH

In the analysis of health expenditures, two input-output relationships are examined: (1) public expenditure on health per capita and life expectancy at age 65 (as a measure of quantity of health), and (2) public expenditure on health per capita and the number of healthy life years at age 65 (as a measure of quality of health).

4.3.1. Life expectancy at 65

Per capita public expenditure on health is positively correlated to life expectancy at age 65. The coefficient of expenditure is rather similar across the three model specifications considered (H1-H3 in Table 4.3), suggesting that country-specific factors may have a limited influence on the outcome. The trend variable in model H1 indicates that efficiency of public expenditure has been improving in the last 15 years. As previously highlighted, given the importance and the different scopes for private health expenditure within national health systems, the analysis also includes a model that accounts for private health expenditure (H3).[23] The estimated coefficient for private health expenditure is both positive and statistically significant. However, given the short time dimension of the panel, the error variance terms in model H3 might be affected by the incidental parameter problem (see footnote 1).

[22] It is difficult, however, to strictly pinpoint these results to an adverse shift in the frontier. The fact that DEA calculates the frontier year-by-year, implies that DEA methods tend to attribute adverse macro shocks to a decline in technology. SFA would instead attribute them to changes in technical efficiency. For further details on this, see Coelli et al. (2005).

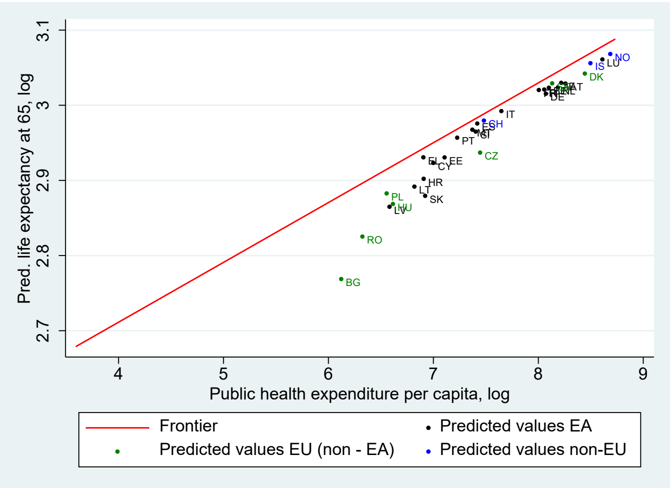
[23] Additional specifications have been tested to cater for environmental and social risks. A few examples include tobacco and alcohol consumption, body mass index and food consumption habits. While not all of them turned out to be relevant, public expenditure on health remained significant. As for the education regressions, this reassures against omitted variable bias.

Table 4.3. **Stochastic frontier analysis of health expenditure**

	Life expectancy at 65			Healthy life expectancy at 65		
	H1 Common frontier	H2 (baseline) country specific frontier	H3 country specific frontier	H4 Common frontier	H5 (baseline) country specific frontier	H6 country specific frontier
Public health expenditure per capita (1 lag 5 years average; log)	0.0796***	0.100***	0.102***	0.237***	0.0751**	0.185**
	(24.21)	(21.88)	(8.88)	(15.55)	(2.79)	(2.89)
Private health expenditure per capita (1 lag 5 year average; log)			0.0339***			0.0528
			(3.68)			(0.72)
trend	0.00140*			-0.00463		
	(2.18)			(-1.61)		
Constant	2.356***			0.729***		
	(91.26)			(5.60)		
Variance of inefficiencies (usigma)	1784	-7.472***	-1232	0.871	-12.92	-5.093***
	(0.26)	(-54.14)	(-1.32)	(0.27)	(-0.16)	(-19.98)
Variance of random error term (vsigma)	-5.756***	-9.349***	-25.82***	-3.029***	-4.374***	-5.644***
	(-51.21)	(-41.24)	(-6.98)	(-23.13)	(-65.52)	(-25.40)
Signal-to-noise ratio	43.378***	2.557***	218367.6***	7.028**	0.014	1.317***
Observations	493	493	266	452	452	257
Average number of years	15.9	15.9	8.9	14.6	14.6	8.6
Number of countries	31	31	30	31	31	30

Note: Standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1. Significant standard deviations of the inefficiency terms (usigma) and significant signal to noise ratios indicate the existence of inefficiencies. All models are estimated using STATA command "sfpanel". Common frontier models (H1 and H4) estimated assuming a time variant technology specified as in Battese and Coelli (1995). Country specific frontier model (H2, H3, H5 and H6) estimated with a fixed effect parameter as in Greene (2005a).

Graph 4.8. **Life expectancy at 65 on health expenditure per capita – 2021**

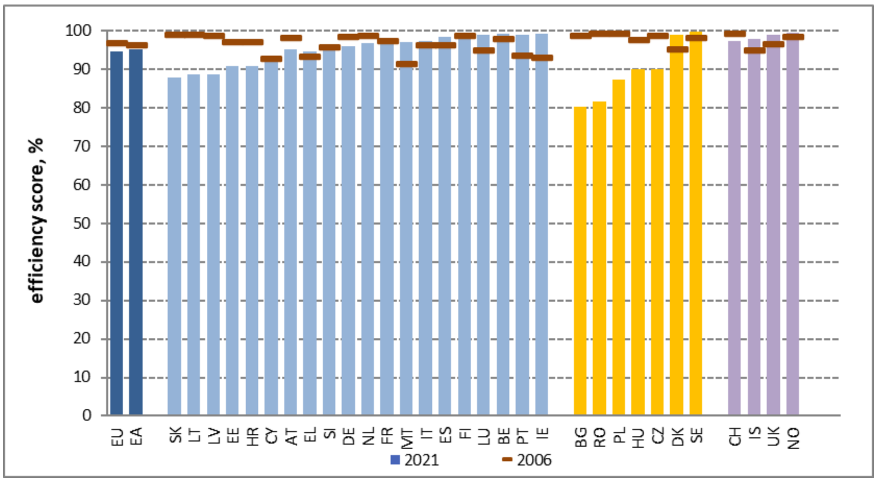


Note: Observations distance from the estimated frontier can be interpreted as how many additional years of life expectancy at 65 could be achieved in a country with the same amount of average spending. Results distinguish between EA countries (black), EU countries not adopting the euro (green) and non-EU countries (blue). Frontier based on common frontier model H1 reported in Table 4.3.

The log-linearised efficient frontier lies above the observed data points (Graph 4.8). As previously explained, this implies that the frontier is determined by observations from an earlier period, indicating a decline in efficiency over time. Nonetheless, most countries are relatively close to the common frontier (based on model H1 in Table 4.3). A few EU countries outside of the EA appear less efficient compared to both EA and non-EU countries. However, as for education, this should be interpreted cautiously. The assumption of a common EU production frontier might be too restrictive, representing an extreme case, and a linearised specification might not accurately approximate the production function at all levels of input.

When allowing for country-specific frontiers, the overall picture remains relatively stable overtime (Graph 4.9). In 2006, the efficiency of public expenditure on health was already quite high, averaging 97% for the EU and 96% for the EA. However, due to the first reduction in life expectancy registered during the COVID-19 pandemic, figures for both the EU and the EA have decreased by around 2 pps.[24] At the country level, a few cases might need some attention. 6 MS have experienced efficiency reductions of over 10 pps, with BG and RO showing significant declines of 18 and 17 pps, respectively. Non-EU countries have appeared relatively more efficient than EU countries. The country-specific frontiers are based on model H2 reported in Table 4.3.

Graph 4.9. **Efficiency scores related to life expectancy at 65 and health expenditure per capita**



Note: 2018 data for UK. EU and EA are based on unweighted averages as all the indicators involved in the estimation of the efficiency scores are measured per capita.

As done above for education, DEA is used to mimic SFA estimations (Graph 4.10). However, given the sharp fall in life expectancy experienced across the EU in 2020 due to the COVID-19 crisis and the corresponding increase in public expenditure on health, DEA estimations exclude these turbulent years from the sample. Due to DEA being essentially a cross-sectional estimation method, including these observations would excessively bias the results. Therefore, estimations D.H1 and D.H2 take life expectancy at 65 in 2019 as output variable. The input variable is the lagged 5-year average (2014-2018) of per capita public expenditure on health in D.H1 (following SFA model H1 of Table 4.3), to which per capita private expenditure on health is added as a second input in estimation D.H2.

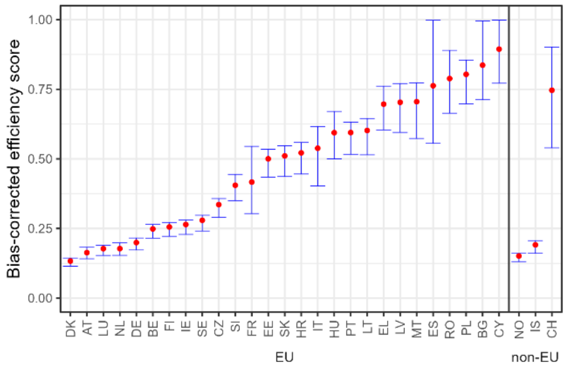
There seems to be a stark contrast between DEA results and the ones obtained from SFA. This is explained by the different assumptions on returns to scale. When allowing for variables returns to scale, as for example in D.H1, BG's and RO's efficiency scores are in the top four positions, while with SFA (and

[24] Whether this reduction is to be considered permanent is beyond the scope of this exercise and probably too early to be addressed.

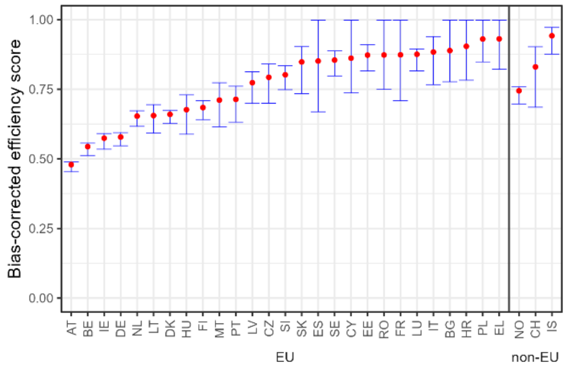
hence constant returns to scale) they turned out to be the two countries farthest away from the predicted efficiency frontier (compare with Graph 4.8). As already argued for education, these countries belong to the lower part of the spending distribution (see Graph A.4 in the Annex) and may therefore be favoured by the non-linearity of the frontier estimated by DEA.

Graph 4.10. **Bias-corrected DEA efficiency scores with life expectancy at 65 as output**

(D.H1)



(D.H2)



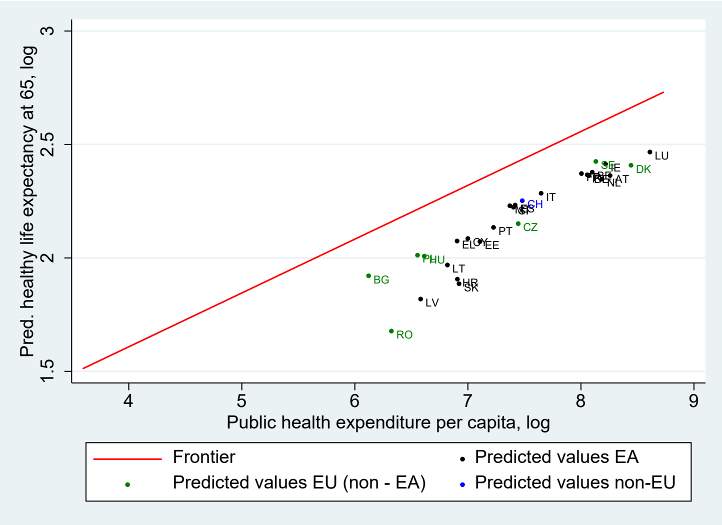
Note: The output variable is life expectancy at 65 in the year 2019. The input variable in D.H1 is the 5-year average (2014-2018) of public expenditure on health (COFOG). D.H2 includes the 5-year average (2014-2018) of private expenditure on health as a second input. Blue error bars indicate 95% confidence intervals.

4.3.2. Healthy life expectancy at 65

The number of years of healthy life expectancy at the age of 65 is positively correlated with per capita public expenditure on health as shown in models H4-H6 in Table 4.3. When focusing on the qualitative outcome, measured here as years of healthy life expectancy at age 65, the coefficient of public expenditure on health is estimated to be larger under the assumption of a common frontier (H4). This highlights the importance of country-specific factors in assessing expenditure efficiency as the common frontier might be mis-specified because of omitted controls, the effects of which might be captured by the expenditure coefficient. The negative coefficient for the trend variable indicates that efficiency might have been decreasing during the analysed period. The baseline model (H5), which includes fixed effects to control for time-invariant factors, results in a smaller coefficient for public expenditure. While the coefficient for private expenditure in model H6 is positive, it is not statistically significant. The short time dimension of the panel and the potential bias because of the incidental parameter problem remain valid concerns (see footnote 1). Moreover, when dealing with years of healthy life expectancy at 65, it might be of interest to focus on the long-term care component of the expenditure (included in the input variable considered).

The log-linearised efficient frontier is positioned above the observed data points also in the case of healthy life expectancy (Graph 4.11). Similar to life expectancy at age 65, this suggests a decline in efficiency over time. In 2022, countries appear farther from the frontier compared to the results illustrated in Graph 4.8. The distance from the estimated frontier is very similar across the three country groups analysed (EA, EU but non-EA and non-EU). The common frontier is derived from model H4, as reported in Table 4.3.

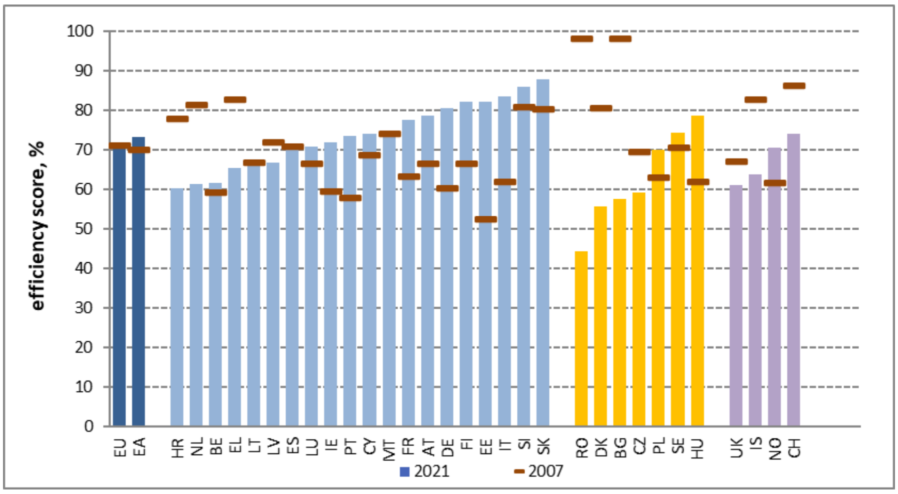
Graph 4.11. **Healthy life expectancy at 65 on health expenditure per capita – 2021**



Note: Observations distance from the estimated frontier can be interpreted as how many additional years of healthy life expectancy at 65 (as measured by PISA) could be achieved in a country with the same amount of average spending. Results distinguish between EA countries (black), EU countries not adopting the euro (green) and non-EU countries (blue). Frontier based on common frontier model H4 reported in Table 4.3.

The analysis of efficiency based on country-specific frontiers reveals highly diverse dynamics across countries (Graph 4.12). These frontiers are derived from the baseline model H5, as reported in Table 4. While the aggregate efficiency levels for both the EU and the EA have remained stable, on average, at 70 percent indicating limited improvement and scope for further gains, the country-level evidence is more differentiated. 18 countries in the sample have improved their relative efficiency, with an average increase of 11 pps (the highest being EE with an improvement of more than 29 pps). Conversely, 12 countries have seen their relative efficiency reduced compared to their 2007 levels. The average reduction is around 17 pps with a couple of sharp declines in the case of RO and BG, dropping from nearly full efficiency to 44 and 55 percent, respectively. In 2021, none of the countries considered is above 90% of the potential efficiency and only 6 (DE, FI, EE, IT, SI, SK) above 80%.

Graph 4.12. **Efficiency scores related to healthy life expectancy at 65 and health expenditure per capita**

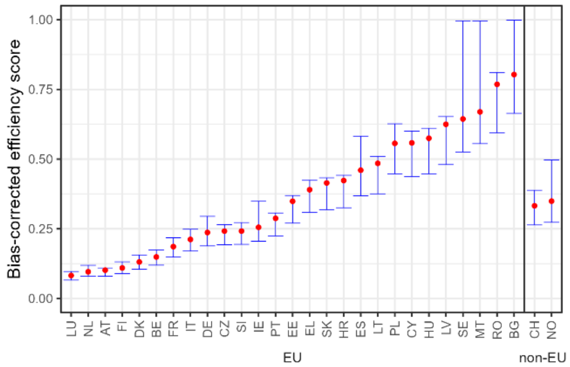


Note: 2010 data for HR, 2018 data for IS and UK and 2020 data for NO. EU and EA are based on unweighted averages as all the indicators involved in the estimation of the efficiency scores are measured per capita.

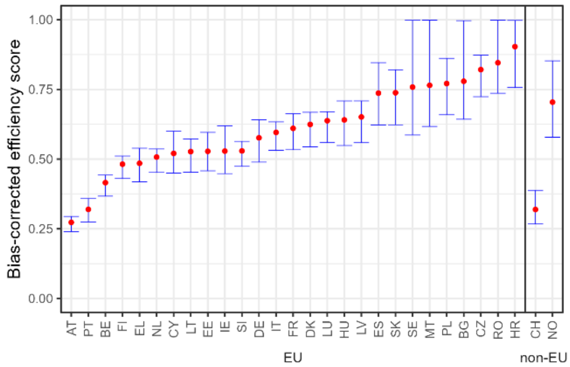
DEA results are again somewhat in contrast with those obtained with SFA. The second group of DEA estimations, D.H3 and D.H4 (Graph 4.13) are analogous to the first group, except that they use *healthy* life expectancy at 65 as input. As for model D.H2, model D.H4 includes private expenditure on health as a second input. In the single-input model (D.H3), SE, MT, RO and BG obtain the four highest efficiency scores. A look at the distribution of expenditure on health against healthy life expectancy (Graph A.5 in the Annex), reveals again that these countries lie indeed close to a non-linear frontier that envelops the observations (a clear hint that variable returns to scale might play a role).

Graph 4.13. **Bias-corrected DEA efficiency scores with healthy life expectancy at 65 as output**

(D.H3)



(D.H4)



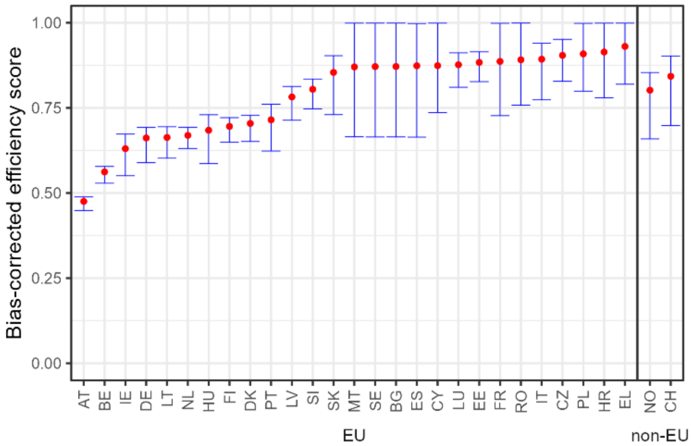
Note: The output variable is healthy life expectancy at 65 in the year 2019. The input variable in D.H1 is the 5-year average (2014-2018) of public expenditure on health (COFOG). D.H2 includes the 5-year average (2014-2018) of private expenditure on health as a second input. Blue error bars indicate 95% confidence intervals.

4.3.3. Health overall (multi-output DEA)

The analysis now turns again to a multi-output and multi-input DEA estimation that includes both the output variables used above (life expectancy and healthy life expectancy, at 65) as well as both input variables (public and private health expenditure, per capita). The time period chosen is the same as above: 2019 for the two output variables and the 5-year average 2014-2018 for the two input variables. The results are shown in Graph 4.14. EL, HR and PL obtain the highest efficiency scores, although the fact that many countries have close scores and the presence of large confidence intervals make the result uncertain.

Graph 4.14. **Bias-corrected efficiency scores from multi-output DEA (health)**

(D.H5)



Note: the output variables are life expectancy at 65 and healthy life expectancy at 65 in 2019. The input variables are the 5-year averages (2014-2018) of: i) public expenditure on health (COFOG) and ii) private expenditure on health. Blue error bars indicate 95% confidence intervals.

Table 4.4. **Malmquist indices of changes in efficiency of health spending 2008-2019**

DMU	MI	PTEC	TC	DMU	MI	PTEC	TC
AT	0.95	0.72	1.32	IT	1.30	1.64	0.79
BE	0.99	1.11	0.89	LT	0.75	0.98	0.76
BG	0.62	1.00	0.62	LU	1.02	1.20	0.85
CY	1.28	1.03	1.24	LV	0.98	1.58	0.62
CZ	0.86	0.92	0.93	MT	0.96	1.40	0.69
DE	0.91	1.10	0.83	NL	1.06	1.10	0.96
DK	0.97	0.96	1.00	PL	0.82	0.89	0.93
EE	0.74	0.94	0.79	PT	1.31	1.33	0.99
EL	1.88	1.58	1.19	RO	0.62	0.89	0.70
ES	1.26	1.89	0.67	SE	1.37	3.79	0.36
FI	1.05	1.04	1.01	SI	1.00	0.94	1.07
FR	1.10	0.55	2.02	SK	1.03	1.62	0.64
HU	1.05	1.31	0.80	CH	0.69	0.90	0.77
IE	1.37	2.05	0.67	NO	1.08	0.50	2.16

Note: MI = Malmquist index; PTEC = Pure technical efficiency change; TC = Technological change. MI=PTEC·TC. Values above (below) one indicate an increase (decrease) in efficiency. The input and output variables are the same as in estimation D.H5, excluding private health expenditure.

Finally, Table 4.4 shows the Malmquist index of changes in efficiency between 2008 and 2019 (time period chosen to maximise sample size). This model considers both output variables used so far (as in estimation D.H5 reported in Graph 4.14), but only public expenditure as input, because of limited data availability on private expenditure. Half of the countries in the sample show a decreased efficiency score, whit BG, RO and CH occupying the bottom positions, while the other half shows an improvement, with the highest scores obtained by EL, IE and SE. As observed for education, there seems to have been an adverse shift in the technological frontier, with all but eight countries obtaining a TC score below one.[25]

5. CONCLUSION

Efficient allocation of public finances is essential to enhance economic development, productivity, and the well-being of people. This is all the more true in sectors like education and health, which have also been heavily affected by the recent CoVID-19 pandemic. This study performed an empirical analysis of the efficiency of public spending in these two sectors, by using Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). For each sector, two output measures were used: one reflecting the *quantitative* dimension of the outcome, the other reflecting the *qualitative* dimension.

Some stylised facts emerged from the analysis:

- Concerning education:
    a. Over the sample period, there is an observed increase in efficiency of education spending with respect to the quantity of education, measured by tertiary education attainment rates, while a decline in efficiency is registered with respect to the quality of education, proxied by PISA scores.
    b. The SFA analysis indicates that, for what concerns attainment rates, most of the countries are operating close to their respective country-specific efficiency frontiers. In contrast, significant efficiency gaps are evident when examining PISA scores.
    c. DEA analysis suggests the presence of decreasing returns to scale in the relation between education spending and both the *quantity* and *quality* of education. This finding is not corroborated by the SFA-based common frontier analysis. However, it is important to acknowledge the caveats previously noted regarding the differences between SFA and DEA, notably in how the two differ with regard to return to scale assumptions and the shape of the frontier (linear versus piece-wise linear).
    d. The Malmquist Index, obtained by a multi-output approach where both tertiary attainments and PISA scores are simultaneously considered as output variables, indicates that a majority of countries in the sample have experienced a decrease in efficiency relative to education spending. This decline appears to be partly attributable to an adverse shift in the technological frontier, coherently with the negative trend observed in recent years for PISA scores.
- Concerning health:
    a. Over the sample period, the SFA method shows an improved efficiency for what concerns life expectancy at 65, whereas the opposite trend is observed for the expected number of years spent in good health.

[25] As already explained in footnote 22, DEA methodology tends to attribute adverse macro-shocks to a decline in technology.

b. Countries are generally close to their respective country-specific efficiency frontiers in achieving long life expectancy, while significant gaps are evident concerning expected years spent in good health. The observed efficiency of public spending on health as regards life expectancy at 65 suggests that there is generally not much to expect in terms of savings potential for public finances.

c. Despite some setback due to the COVID-19 pandemic, public expenditure on health remains efficient in producing years of life expectancy (at age 65). On average, EU and EA countries operate at 95 percent of their relative capacity.

d. Similarly to findings in education, DEA analysis hints at the fact that assuming decreasing returns to scale in health spending might be more appropriate.

e. The evolution of spending efficiency over time, as estimated via the Malmquist index – utilising both life expectancy and healthy life expectancy as output variables – presents a mixed picture, with the sample divided in half between countries that improved their efficiency and those that experienced declines. As observed in education, total efficiency changes appear to have been influenced by an adverse shift in the technological frontier. Since Malmquist estimation excludes the years impacted by the CoVID-19 pandemic, this suggests the presence of other important factors that adversely affected the efficiency of the health sector already prior to the pandemic.

These findings leave some open questions and pave the way for further analysis on the topics. For instance, further research could investigate the reasons behind the recent increase in the *quantity* of education (higher attainment rates) alongside the decline in educational *quality*, as measured by the PISA scores. Taking into account countries' specificities (especially in the health sector), overcoming a few of the assumption implied by the adopted methodologies (i.e. homogeneity and access to the same technology of production), might be of interest. Investigating what has been driving past trends of inefficiency is also left to future investigation as well as the possibility of exploiting different datasets or input and output variables.

REFERENCES

Afonso, A., & Kazemi, M. (2017). Assessing public spending efficiency in 20 OECD countries. In B. Bökemeier, & A. Greiner (Eds.), *Inequality and Finance in Macrodynamics* (pp. 7-42). Springer International Publishing.

Afonso, A., & St. Aubyn, M. (2005). Non-parametric approaches to education and health efficiency in OECD countries. *Journal of Applied Economics, 8*(2), 227-246.

Afonso, A., & St. Aubyn, M. (2006). Cross-country efficiency of secondary education provision: a semi-parametric analysis with non-discretionary inputs. *Economic Modelling, 23*(3), 476-491.

Afonso, A., & St. Aubyn, M. (2006). Cross-country efficiency of secondary education provision: A semi-parametric analysis with non-discretionary inputs. *Economic Modelling*, 476-491.

Afonso, A., & St. Aubyn, M. (2011). Assessing health efficiency across countries with a two-step and bootstrap analysis. *Applied Economics Letters, 18*(15), 1427-1430.

Agasisti, T. (2014). The Efficiency of Public Spending on Education: an empirical comparison of EU countries. *European Journal of Education, 49*(4), 543-557.

Aigner, D., Lovel, C. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, 21-37.

Amado, C. A., & Dyson, R. G. (2008). Exploring the use of DEA for formative evaluation in primary care with an example from the Portuguese NHS. *Journal of the Operational Research Society, 59*(5), 563-575.

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Management Science, 30*(9), 1078-1092.

Battese, G., & Coelli, T. (1992). Frontier Production Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India. *The Journal of Productivity Analysis*(3), 135-169.

Canton, E., Thum-Thysen, A., & Voigt, P. (2018). Economists' Musings on Human Capital Investment: How Efficient is Public Spending on Education in EU Member States? *European Economy Discussion Papers*(081).

Caves, D. W., Christensen, L. R., & Diewert, E. W. (1982). Multilateral Comparisons of Output, Input, and Productivity Using Superlative Index Numbers. *The Economic Journal, 92*(365), 73-86.

Cepparulo, A., & Mourre, G. (2020). How & How Much? The Growth-Friendliness of Public Spending Through the Lens. *European Economy Discussion Papers*(132).

Charnes, A., Cooper, W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, 429-444.

Coelli, T. J., Prasada Rao, D., O'Donnell, C. J., & Battese, G. E. (2005). *An Introduction to Efficiency and Productivity Analysis - Second edition.* Springer.

Cooper, Z., Gibbons, S., Jones, S., & McGuire, A. (2011). Does hospital competition save lives? Evidence from the English NHS Patient Choice Reforms. *The Economic Journal, 121*(554), 228-260.

Cordero-Ferrera, J. M., Pedraja-Chaparro, F., & Simancas, R. (2011). Efficiency and equity in the provision of public education. *Economics of Education Review, 30*(2), 254-272.

De Witte, K., & López-Torres, L. (2017). Efficiency in education: a review of literature and a way forward. *Journal of the Operational Research Society, 68*(4), 339-363.

Dutu, R., & Sicari, P. (2016). Public Spending Efficiency in the OECD: Benchmarking Health Care, Education and General Administration. *OECD Economics Department Working Papers No. 1278*.

European Commission, Directorate-General for Education, Youth, Sport and Culture. (2023). *Investing in education 2023.* Publications Office of the European Union. doi:https://data.europa.eu/doi/10.2766/529409

European Commission, Directorate-General for Education, Youth, Sport and Culture. (2024). *The twin challenge of equity and excellence in basic skills in the EU - An EU comparative analysis of the PISA 2022 results.* Publications Office of the European Union. doi:https://data.europa.eu/doi/10.2766/881521

Farrell, J. (1957). The Measurement of Productive Efficiency. *Journal of the Royal Statistical Society. Series A (General), 120*(3), 253-290.

Greene, W. (2005a). Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of Econometrics*(126), 269-303.

Greene, W. (2005b). Fixed and Random Effects in Stochastic Frontier Models. *Journal of Productivity Analysis, 23*, 7-32.

Jayasuriya, R., & Wodon, Q. (2003). Efficiency in education expenditure: a review of cross-country evidence. *World Bank Policy Research Working Paper*.

Medeiros, J., & Schwierz, C. (2015). Efficiency estimates of health care systems. *European Economy Economic Papers*(549).

Meeusen, W., & van den Broeck, J. (1977). Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error. *International Economic Review*, 435-444.

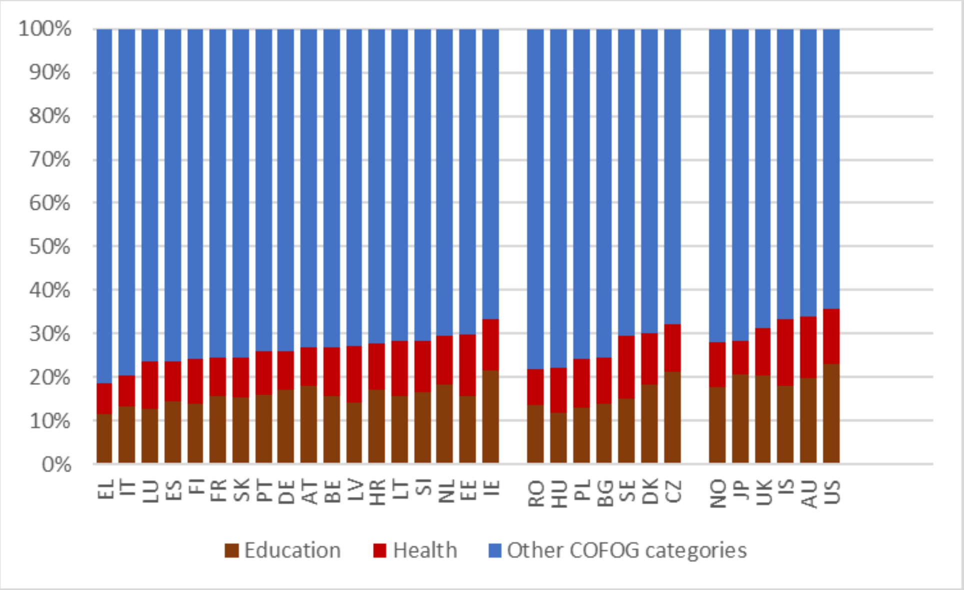
Serrano-Cinca, C., Mar-Molinero, C., & Iturralde, T. (2005). Measuring DEA efficiency in internet companies. *Decision Support Systems, 38*(4), 557-573.

Simar, L., & Wilson, P. (1998). Sensitivity analysis of efficiency scores: how to bootstrap in nonparametric frontier models. *Management science*(44), 49-61.

Stevens, P. (2005). Assessing the performance of UK higher education: stochastic frontier analysis and DEA. *Applied Economics, 37*(17), 1875-1888.

A. ANNEX

Graph A.1. Composition of expenditure - 2021



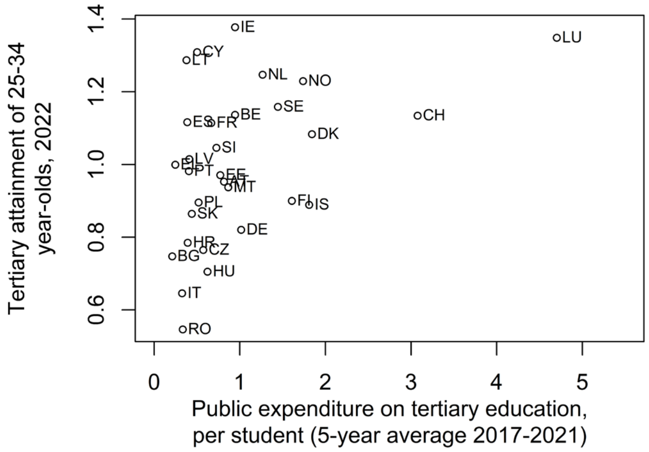
Source: OECD - COFOG expenditure data.

Table A.1. **Stochastic frontier analysis of education expenditure – Pre COVID-19 period**

	Tertiary educational attainment - age group 25-34			PISA average score		
	ED1 Common frontier	ED2 (baseline) country specific frontier	ED3 country specific frontier	ED4 Common frontier	ED5 (baseline) country specific frontier	ED6 country specific frontier
Public tertiary education expenditure per student (1 lag 5 years average, log)	0.107***	0.344***	0.110***			
	(6.51)	(13.43)	(3.74)			
Public secondary education expenditure per student (1 lag 5 years average, log)				0.0255***	0.372***	0.281***
				(7.10)	(181.39)	(18.47)
Share of the parents with tertiary education (log)			0.690***			0.195***
			(19.37)			(3.74)
Trend	0.0204***			-0.00246**		
	(9.09)			(-2.80)		
Constant	2.457***			6.073***		
	(15.34)			(171.89)		
	0					
Variance of inefficiencies (usigma)	-1.885***	-2.667***	-3.582***	-4.506***	-6.313***	-13.04***
	(-4.72)	(-37.14)	(-51.23)	(-3.32)	(-20.16)	(-15.38)
Variance of random error term (vsigma)	-4.279***	-11.84***	-13.13***	-7.317***	-7.170***	-5.959***
	(-15.87)	(-8.39)	(-8.95)	(-37.18)	(-20.94)	(-44.22)
Signal-to-noise ratio				4.078***	1.535***	0.029***
Observations	482	482	482	277	277	277
Average number of years	15.5	15.5	15.5	8.9	8.9	8.9
Number of countries	31	31	31	31	31	31

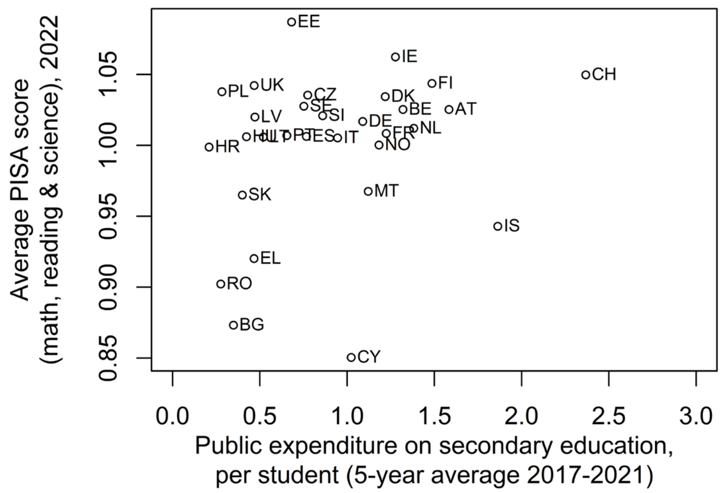
Note: Standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1. Significant standard deviations of the inefficiency terms (usigma) and significant signal to noise ratios indicate the existence of inefficiencies. All models are estimated using STATA command "sfpanel". Common frontier models (H1 and H4) estimated assuming a time variant technology specified as in Battese and Coelli (1995). Country specific frontier model (H2, H3, H5 and H6) estimated with a fixed effect parameter as in Greene (2005a). Regressions performed over a restricted sample covering the period 2000 – 2019.

Graph A.2. **Scatterplot of tertiary attainment of 25–34-year-olds against expenditure on tertiary education**



Note: both variables are divided by their cross-section mean value.

Graph A.3. **Scatterplot of average PISA scores against public expenditure on secondary education**



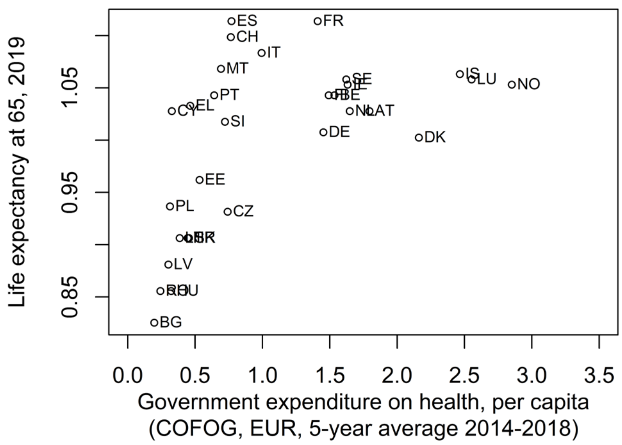
Note: both variables are divided by their cross-section mean value.

Table A.2. **Stochastic frontier analysis of health expenditure – Pre COVID-19 period**

	Life expectancy at 65			Healthy life expectancy at 65		
	H1 Fixed effect (Green 2005)	H2 Fixed effect (Green 2005)	H3 Time variant (BC 95)	H4 Fixed effect (Green 2005)	H5 Fixed effect (Green 2005)	H6 Time variant (BC 1995)
Public health expenditure per capita (1 lag 5 years average; log)	0.115***	0.0860***	0.0765***	0.0737*	0.138	0.232***
	(27.20)	(9.16)	(25.38)	(2.42)	(1.75)	(14.40)
Private health expenditure per capita (1 lag 5 year average; log)		0.0605***			0.120	
		(5.05)			(1.36)	
trend			0.00361***			-0.00425
			(5.49)			(-1.18)
Constant			2.313***			0.759***
			(82.24)			(5.37)
Variance of inefficiencies (usigma)	-15.08	-2385	-7174	-11.53	-4.964***	1018
	(-0.64)	(-0.30)	(-0.25)	(-0.86)	(-14.61)	(0.38)
Variance of random error term (vsigma)	-8.035***	-9.773***	-5.834***	-4.458***	-5.798***	-2.999***
	(-113.14)	(-30.40)	(-84.97)	(-61.88)	(-15.75)	(-22.21)
Signal-to-noise ratio	0.029***	40.202***	0.512	0.029	1.518***	7.452***
Observations	433	204	433	395	198	395
Average number of years	14	7.3	14	12.7	7.1	12.7
Number of countries	31	28	31	31	28	31

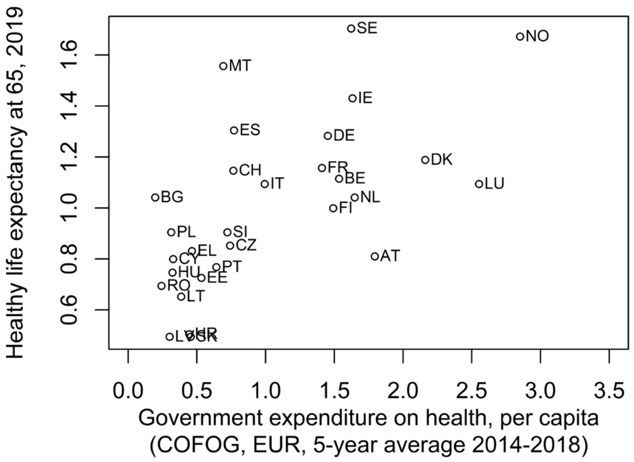
Note: Standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1. Significant standard deviations of the inefficiency terms (usigma) and significant signal to noise ratios indicate the existence of inefficiencies. All models are estimated using STATA command "sfpanel". Common frontier models (H1 and H4) estimated assuming a time variant technology specified as in Battese and Coelli (1995). Country specific frontier model (H2, H3, H5 and H6) estimated with a fixed effect parameter as in Greene (2005a). Regressions performed over a restricted sample covering the period 2006 – 2019.

Graph A.4. **Scatterplot of life expectancy at 65 against public expenditure on health**



Note: both variables are divided by their cross-section mean value.

Graph A.5. **Scatterplot of healthy life expectancy at 65 against public expenditure on health**



Note: both variables are divided by their cross-section mean value.

EUROPEAN ECONOMY DISCUSSION PAPERS

European Economy Discussion Papers can be accessed and downloaded free of charge from the following address: Publications (europa.eu).

Titles published before July 2015 under the Economic Papers series can be accessed and downloaded free of charge from:
http://ec.europa.eu/economy_finance/publications/economic_paper/index_en.htm.

GETTING IN TOUCH WITH THE EU

In person

All over the European Union there are hundreds of Europe Direct Information Centres. You can find the address of the centre nearest you at: http://europa.eu/contact.

On the phone or by e-mail

Europe Direct is a service that answers your questions about the European Union. You can contact this service:

- by freephone: 00 800 6 7 8 9 10 11 (certain operators may charge for these calls),
- at the following standard number: +32 22999696 or
- by electronic mail via: http://europa.eu/contact.

FINDING INFORMATION ABOUT THE EU

Online

Information about the European Union in all the official languages of the EU is available on the Europa website at: http://europa.eu.

EU Publications

You can download or order free and priced EU publications from EU Bookshop at: http://publications.europa.eu/bookshop. Multiple copies of free publications may be obtained by contacting Europe Direct or your local information centre (see http://europa.eu/contact).

EU law and related documents

For access to legal information from the EU, including all EU law since 1951 in all the official language versions, go to EUR-Lex at: http://eur-lex.europa.eu.

Open data from the EU

The EU Open Data Portal (http://data.europa.eu/euodp/en/data) provides access to datasets from the EU. Data can be downloaded and reused for free, both for commercial and non-commercial purposes.

Publications Office
of the European Union