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University of Naples Federico II

University of Salerno

Bocconi University, Milan

CSEF - Centre for Studies in Economics and Finance
DEPARTMENT OF ECONOMICS AND STATISTICS – UNIVERSITY OF NAPLES FEDERICO II
80126 NAPLES - ITALY
Tel. and fax +39 081 675372 – e-mail: csef@unina.it
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# *School productive performance and technology gaps: new evidence from PISA 2018*

**Salvatore Capasso[*], Maria Kaisari[†], Konstantinos Kounetas[‡], and Elias Lainas[§]**

**Abstract**
Improving educational outcomes is a global political imperative due to its favourable influence on a country's economic prosperity. Although researchers have endeavoured to gauge school performance through diverse data resources and techniques, there remains a lack of clarity regarding the factors that enhance school effectiveness. Using the latest version of the Programme for International Student Assessment (PISA, 2018), this paper employs a bootstrapped data envelopment analysis (DEA) to investigate the factors underlying the performance of 8825 schools across 34 OECD countries in terms of their national and international technological capabilities. The central idea is that technological heterogeneity and the technology gap significantly influence the benchmarking process. The findings confirm the presence of substantial technology gaps, indicating that the examined schools are unable to fully harness their potential due to limitations in metatechnology. These gaps are influenced by student characteristics, school features and educational practices.

**JEL Classification:** D24, O13, O47, Q40.

**Keywords:** Bootstrap Data Envelopment Analysis, School's productive performance, Technology gap, PISA

[*] CNR, University of Naples Parthenope, and CSEF. Email: scapasso@uniparthenope.it (*Corresponding author*)

[†] University of Patras.

[‡] University of Patras and ISMed CNR.

[§] University of Patras.

## 1 Introduction

Enhancing school performance has become a political priority in numerous countries, as the quality of education has a positive impact on economic performance (Hanushek and Kimko, 2000). The advent of globalization has provided increased opportunities for countries with advanced education systems, while the integration of computing and communication technologies has brought about significant changes in traditional educational practices. The COVID-19 pandemic, with its widespread closure of in-person activities, has acted as a crucial test for educational systems, prompting the exploration of new alternatives (Sut and Oznacar, 2021; Henriques et al., 2022). Furthermore, the simultaneous occurrence of a technology-driven revolution (Industry 4.0) and a value-driven revolution (Industry 5.0) raises important questions and demands attention in the field of education. These transformations are becoming more evident as national school systems grapple with concerns about the adequacy of current schooling models, which in turn contribute to the accelerated pace of technological and scientific advancements.

In numerous countries, educational systems have undergone organizational restructuring and operational changes, transitioning from isolation to collaboration (Nordholm, 2016). This shift towards collaboration aims to foster knowledge transfer and enhance school performance by establishing networks (Muijs, 2010), forming school federations, and promoting international agreements and cooperation (Nordholm, 2016). Additionally, the active participation of many countries in international large-scale surveys like PISA provides researchers with an opportunity to investigate various aspects of school performance evaluation (e.g., Agasisti and Zodio, 2018; 2019; Cordero et al., 2020). However, most of these studies primarily focus on estimating technical efficiency, neglecting the significance of technology heterogeneity.

The analysis of country-level PISA efficiency results provides only partial information due to limited knowledge at the national production frontiers (Agasisti and Zoido, 2018; 2019). The COVID-19 experience has confirmed the existing belief that knowledge is not confined to national frontiers alone, and additional hierarchical production frontiers serve as supplementary sources (Chatzistamoulou et al., 2022). In our study, we propose that metatechnology (metafrontier) represents a pool of knowledge that encompasses the relative complexity and diversity of knowledge associated with national technologies (Castellacci, 2007; Castellacci et al., 2014; Cordero et al., 2017; Chatzistamoulou et al., 2022;). By utilizing metatechnology as a global benchmark, we address the issue of existing technological heterogeneity while disregarding national production structures (Tsekouras et al., 2017; Burger et al., 2022; Chatzistamoulou et al., 2022). Furthermore, our approach allows consideration of potential spillover effects that arise within the context of metatechnology (Tsekouras et al., 2016; 2017) and technology flows (Tsekouras et al., 2017; Chatzistamoulou et al., 2022). To the best of our knowledge, this dimension of evaluating school productive performance in PISA waves has not been previously explored.

The main contribution of this study is that we examine country heterogeneity in school productive performance by using a bootstrapped DEA under a metatechnology framework. In this vein, we consider free and available knowledge flows from denser (international) to sparser (national) technology structures from which any school can benefit. Thus, the role of knowledge transfer and spillovers, absorptive capacity and technological capabilities comes into play in defining the extent of a school's technology gap. In addition to analyzing productive performance measures based on international and national technology and deriving country rankings, we also investigate the variables that contribute to reducing or increasing the technology gap in schools. Therefore, we examined three distinct categories of variables: student characteristics, school features, and school practices and processes. These categories encompass a range of factors that may influence the technology gap in schools.

The empirical results of the paper confirm the existence of three main clusters within the countries examined: the champions, the followers and the laggards. However, the results vary significantly depending on the technology structure examined while the estimates regarding the international frontier signify important potentials for improvement. Also, our results reveal significant technology gaps denoting the inability of the schools examined to exploit their potential due to metatechnology. This inability can be explained using the concepts of absorptive capacity, and technological capabilities. Finally, several variables with a greater or lesser degree of importance from the three different categories seem to have an effect (negative or positive) on the technology gap.

The rest of the paper is organized as follows. The next section presents a short literature review while Section 3 briefly describes the main features of educational systems around the globe. Section 4 presents the empirical background for our analysis and Section 5 describes data sources and provides summary statistics. Section 6 discusses the results while Section 7 concludes.

## 2 Short review of the literature

Numerous studies are dedicated to examining the concept of schooling, whether it pertains to individual students, schools or a country's overall educational effectiveness. One of the pioneering studies in this area was conducted by Wößmann (2003), who utilized a combination of international student data and school-level micro-data from multiple countries. Since then, many more researchers have adopted a cross-country approach to explore various aspects of educational achievement. For instance, Hanushek (2005) took a comprehensive view of school quality and employed panel data from TIMSS and PISA to investigate the subject in Germany. Similarly, Ammermüller et al. (2005) utilized TIMSS data for seven Eastern European countries and discovered that a student's background has a greater impact on educational performance compared to school resources. These types of studies employ econometric techniques to establish causal relationships between variables such as student background, school environment and educational outcomes, typically measured through test scores.

Previous empirical research has predominantly focused on various school-related factors, including class size (Angrist and Lavy, 1999; West and Wößmann, 2006; Krassel and Heinesen, 2014; Blatchford and Webster, 2018), teacher-student ratio (Sibiano and Agasisti, 2013; Agasisti and Zodio, 2015; Aparicio et al., 2019; Cordero et al., 2018, 2020), school facilities (McGowen, 2007; Aparicio et al., 2019; Royo and Fajardo, 2020; Cordero et al., 2020), students' backgrounds (Brunello and Checchi, 2005; Mazzonna, 2014; Agasisti and Zodio, 2015, 2019; Aparicio et al., 2019; Cordero et al., 2018, 2020), and the performance disparities between private and publicschools (Vandenberghe and Robin, 2006; West and Wößmann, 2006). In recent decades, researchers have gained easier access to international databases containing educational data such as PISA, TIMSS and PIRLS. By utilizing cross-sectional data aggregated at the national level, scholars aim to assess the effectiveness of educational systems (Clements, 2002; Afonso and Aubyn, 2006; Giambona et al., 2011; Agasisti, 2014; Gimenez et al., 2007, among others) using frontier methods.

Nevertheless, there exist studies that assess and compare the efficiency of educational systems across countries by utilizing school-level data. For instance, Cordero et al. (2020) examined the performance of schools in OECD countries that participated in PISA 2015. Their comprehensive dataset included 9,369 schools and revealed that school resources and environmental factors contribute to a country's position on the efficiency scale, as determined by students' test scores. Agasisti and Zoido (2015) employed 2012 PISA data from 28 developing countries, encompassing a sample of over 6,800 schools.

They found that, on average, schools operated at 70% leaving a 30% potential for improvement in resource utilization. Their study also unveiled significant correlations between estimated efficiency and factors such as student characteristics (e.g., truancy), teachers' practices (e.g., extracurricular activities), and certain school characteristics (e.g., location and ownership status, public or private). Lastly, Hanushek et al., (2013) analyzed school autonomy using four waves of PISA data, distinguishing between well-developed and low-performing educational systems.

In recent years, several studies have examined the performance of schools in different countries using various data sources. Sutherland et al. (2010) assessed the performance of schools in thirty OECD countries participating in PISA 2003. Aparicio et al., (2017) utilized data from OECD countries participating in PISA 2012 and discovered varying levels of inefficiency for different outcomes, specifically test scores in reading and mathematics. Interestingly, their results indicated that schools in OECD countries tend to be more efficient in mathematics compared to reading. Agasisti and Zoido (2015) conducted an efficiency measurement study involving over 8,600 schools across thirty countries participating in PISA 2012. On analyzing the data in their final dataset, the authors found that, on average, test scores in mathematics and reading could be increased by approximately 27% if schools effectively utilized their available resources. Furthermore, some studies have focused on a smaller sample of countries. For example, Delprato and Antequera (2021) utilized data from PISA for Development 2017, encompassing seven developing countries. Their findings revealed that cognitive and non-cognitive scores could potentially be increased by twenty and twenty-two percent, respectively, while holding the inputs constant. These studies collectively contribute to our understanding of school performance and the potential for enhancing educational outcomes across different countries and contexts.

Examining the specific case of Spain, Aparicio et al., (2017) conducted a study using a final sample of 902 schools that participated in PISA 2012. Their focus was on measuring the technical efficiency of these schools. Employing an output-oriented approach, they found that the Spanish sample had the potential to increase their outputs (reflected in students' test scores) by twelve percent without making any changes to their existing resources. Similarly, in the context of Uruguay, Santin and Sicilia (2012) analyzed 132 secondary schools using data from the third cycle of PISA in 2009. The findings indicated an average inefficiency of 7.5% for the Uruguayan schools. The study emphasized the importance of student motivation as a key factor in enhancing efficiency, suggesting that encouraging students to devote more time to reading outside school hours could help reduce inefficiencies.

In addition to the conventional factors related to schools and students, researchers have explored the impact of country-level variables as contextual factors on efficiency outcomes. These variables tend to vary across countries, although some groups of countries may exhibit similar values for such variables. For example, Cordero et al., (2018) incorporated country-level economic variables such as gross domestic product (GDP) per capita and public expenditure per student in secondary education, as well as cultural variables such as attitudes towards hard work and responsibility. Their study revealed that all economic and cultural variables had a significant impact on efficiency levels. Consequently, country factors play a more prominent role in explaining differences in school efficiencies due to greater heterogeneity between countries compared to within-country variations. These findings align with the existing literature, such as the work of Afonso and Aubyn (2006), which demonstrates that economic factors explain differences in school efficiencies between countries. Likewise, cultural factors also contribute significantly to variations across countries, as highlighted by Mendez (2015). A similar study was conducted by Coco and Lagravinese (2014), which included the usual school and student variables commonly used in such studies, along with additional country-level variables like the unemployment rate. Notably, they introduced the concept of cronyism as a contextual variable to examine its potential to explain inefficiency scores across 34 OECD countries. Through a second-stage analysis, similar to the studies mentioned above, they demonstrated a significant and positive relationship between cronyism and inefficiency scores.

The majority of the above studies employ frontier and non-parametric techniques, such as Free Disposal Hull (FDH) or Data Envelopment Analysis (DEA), to assess the efficiency of decision-making units. Such techniques offer the necessary flexibility to handle multiple inputs and outputs simultaneously, making them well-suited to measuring educational system efficiencies. Given that educational systems typically involve multiple inputs and outputs; these techniques are preferred in such studies. Furthermore, some studies take a two-stage approach, wherein they conduct a second-stage analysis to examine the potential influence of contextual variables on efficiency estimates. This approach is observed in studies by Afonso and Aubyn (2006), Agasisti (2014), Bogetoft et al., (2015), Agasisti and Zoido (2018), Aparicio et al., (2018), and Cordero et al., (2018), among others.

In recent decades, scholars have extensively examined institutional theory both in society and economics. Studies by Meyer and Rowan (1977), Myrdal (1978), Williamson (1985), Zucker (1987), Tolbert and Zucker (1999), Coase (1998), Acemoglu and Robinson (2006), and Richter (2015) have shed light on the power and influence of institutional processes. Institutional change, a well-researched aspect, has been identified as a complex process characterized by persistence, wherein institutional practices can undergo changes alongside institutional continuity (North, 1993; Acemoglu and Robinson, 2006). Within the realm of institutional theory, education and its structures constitute a distinct branch of inquiry (Meyer, 1977). Meyer and Rowan (2006) delve deeply into institutional practices in education and the challenges associated with implementing changes. Numerous researchers have highlighted the difficulty of instituting transformative changes in primary and secondary education (Gamson et al., 2015; Reimers, 2020) as well as higher education (Enders et al., 2013; Chan, 2019). School units, as components of the educational system, embody their own institutional practices (Baker, 2006; Andersen, 2008).

This article emphasizes the significance of enhancing institutional practices, such as adopting innovations and fostering interaction between school units, in improving the efficiency of schools. We focus on the concept of technological gap, which we analyze in detail below. Within this framework, we explore three categories of variables: student characteristics, school features and school practices, all of which reflect the key institutional practices observed in national and international education.

## 3 Some evidence on educational systems around the world

Educational systems vary widely around the world, encompassing differences in curriculum, teaching methods, teacher training and professional development, as well as programmes for equity and inclusion. Achieving a standardized method of evaluation across countries is a challenging task.

PISA, a globally recognized international assessment, evaluates student performance. The test aims to standardize procedures and bridge evaluation differences between educational systems to measure the effectiveness of education in different contexts. PISA is not the only standardized assessment providing a common measure for participating countries. The frequency, format and purpose of standardized tests can vary among countries. Some nations rely heavily on high-stakes exams for student advancement, while others place less emphasis on such assessments. However, there is a shared goal of measuring student performance in core subjects like mathematics, reading and science.

For instance, in the United States, standardized testing plays a significant role in student evaluation and accountability, whereas in Finland, there is less emphasis on high-stakes exams. Several countries participating in PISA, including Germany, Japan and the United Kingdom, utilize a common standardized assessment to gauge student performance in core subjects.

Countries exhibit differences in curriculum frameworks and teaching approaches. For example, Finland emphasizes a more traditional, teacher-centred approach, while South Korea prioritizes student-centred and inquiry-based learning methods. Educational systems also differ in their approaches to teacher training and professional development, with variations in pre-service teacher education, ongoing professional development opportunities and career advancement pathways. Nevertheless, most countries recognize the importance of effective teaching and invest in professional development initiatives to enhance teacher quality. Several countries, such as Canada and Australia, strive to align their curriculum and teaching practices with the skills and competencies assessed in PISA, such as critical thinking, problem-solving and collaboration.

Differences in education policies can be profound. For instance, South Korea has a highly competitive education system with a rigorous curriculum and a strong emphasis on academic achievement. In contrast, Canada has a decentralized education system with autonomous provinces, focusing on inclusive education, bilingualism (English and French) and individualized learning approaches. Most countries ac- knowledge the importance of effective teaching and invest in professional development initiatives to enhance teacher quality. They also vary in their approaches to promoting equity and inclusion in education, implementing strategies to support disadvantaged students, address achievement gaps, and ensure equal access to quality education. Finland, for example, is known for emphasizing equal opportunities, teacher autonomy and a holistic approach to education. It features a less standardized curriculum with a strong focus on student well-being and collaborative learning. PISA strives to assess equity in education by analyzing performance differences across various student backgrounds, including socio-economic status and immigrant status. Many countries endeavour to address inequalities in education outcomes and provide equitable opportunities for all students. Germany adopts various approaches to address equity, such as tracking systems based on academic performance, while Finland endeavours to reduce disparities and promote equal opportunities for all students.

## 4 Theoretical Underpinnings

Our empirical strategy follows a two-stage procedure. In the first stage, we calculate efficiency scores for schools to assess their performance in the educational process relative to both national and international production frontiers. This allows us to estimate the technology gaps associated with their performance. In the second stage, we adopt the approach proposed by Simar and Wilson (2007) and regress these technology gaps against a set of covariates to further analyze their determinants.

To operationalize technology heterogeneity, we focus on schools that operate within their respective country-frontier technologies. However, we also acknowledge that these schools exist within a broader global environment where they can be influenced by other distinct technologies. For instance, schools in countries like Greece, Japan and the United States each operate within their unique country technologies. Nevertheless, it is important to recognize that individual schools within these countries have the capacity to adopt and integrate technological schemes from other technologies that may possess different cultural, social, technological and political paradigms. By considering this interplay between local and global technological influences, we can gain insights into the heterogeneity of technology adoption and incorporation within the educational production functions of schools.

## 4.1 Bootstrap DEA and schools' efficiency and meta- efficiency performance

Efficiency and performance measurement, which are integral to the field of educational economics, have been extensively studied using Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) methodologies. As a result, a substantial body of literature has emerged that discusses the merits and drawbacks of these different methodological approaches (Cook and Seiford, 2009). In the context of DEA, the advantage lies in its ability to handle multiple outputs without the need for information on relative prices and a production function. Each period can be treated as a separate and distinct production segment, allowing the estimation of technical and scale efficiency results (Cook and Seiford, 2009). However, one of the main limitations of DEA, in comparison to SFA, is that it does not account for noise in the data, and traditional hypothesis testing is not feasible unless bootstrapping techniques developed by Simar and Wilson (2007, 2000, 1998) are employed.

We adopt a Bootstrap-DEA (Simar and Wilson, 1999; 2007) approach considering $i-th$ schools, each producing $y=(y_1, y_2, \dots, y_k) \in R_+^K$ outputs using $x=(x_1, x_2, \dots, x_n) \in R_+^N$ input under the following production possibility set $T(x)=\{(x,y): x\ can\ produce\ (y)\}$. The output set is defined as $P(x)=y \in R_+^K, (x,y) \ \in T$. The output-oriented efficiency of a school operating under its national frontier (technology) can then be measured with respect to the output set through the direct output distance function $D_0 = inf\delta > 0: y/\delta \in (P(x))$, defined as

$$\widehat{TE(x,y)} \equiv \widehat{\theta(x,y)} = max\left\{\theta |\ \theta y \leq \sum_{i=1}^{N} \gamma_i x_i ; x \geq \sum_{i=1}^{N} \gamma_i x_i \ for\ \gamma_i\right\} \tag{1}$$

such that $\sum_{i=1}^{N} \gamma_i = 1\,;\ \gamma_i \geq 0, i = 1,2,\dots,N$

Building upon the insights of Simar and Wilson (1999; 2007) regarding the inherent bias in DEA estimators of efficiency, we introduce the concept of bootstrap DEA efficiency scores (Kounetas and Papathanasopoulos, 2013; Kounetas and Napolitano, 2018). This approach aims to address the issue of bias in DEA efficiency estimation by employing bootstrap techniques. By doing so, we can obtain more robust and reliable estimates of efficiency scores, thereby enhancing the accuracy and validity of the analysis. Hence, we calculate the bias for the original DEA estimator for the $i-th$ school as:

$$\widehat{bias_i} = \frac{1}{B}\sum_{b=1}^{K} \theta^*_{i,B}\widehat{(x,y)} - \theta_i\widehat{(x,y)} \tag{2}$$

where B represents the number of bootstrap replications. As a result, a bias corrected estimator of $\theta^*_{i,B}\widehat{(x,y)}$ is given as follows[1]:

$$\widehat{bias_i} = \theta^*_{i,B}\widehat{(x,y)} = 2\theta_{i,B}\widehat{(x,y)} - \frac{1}{B}\sum_{b=1}^{K} \theta^*_{i,B}\widehat{(x,y)} \tag{3}$$

However, each school operating at its own national production possibility set does not stand alone and thus can have access to other possible available $J-th$ technology sets at an international scale defined as the convex hull of $T_1 \cup T_2 \cup \dots T_J$ [2]. Thus, the isolation hypothesis (Tsekouras et al., 2016; 2017) is rejected and the production possibility and meta-technical efficiency scores $TE^M Fi$ can be adjusted accordingly as in Eq. (1). We can define the meta-technology ratio using the following formula:

$$MTR_i(x,y) = \frac{TE^M F_i}{TE_i^F} \tag{4}$$

and the technology gap by the relationship

$$TG_i(x,y) = 1 - MTR_i(x,y) \tag{5}$$

In our study, we utilize a technological hierarchy that encompasses both global/international and national/country technologies (Chatzistamoulou et al., 2022). This hierarchical approach enables us to estimate efficiency scores at both the national and international levels. By considering these different technological levels, we gain insights into the relative performance and efficiency of schools within their respective national contexts as well as in comparison to schools operating on an

[1] An interested reader can find more information in Simar and Wilson (1999; 2000; 2007).

[2] Differences between the DEA and FDH efficiency estimators test the validity of the convexity assumption for the corresponding frontier (Simar and Wilson, 2022). By analyzing the differences between the DEA and FDH efficiency estimators, one can evaluate the validity of the convexity assumption for the corresponding frontier, as suggested by Simar and Wilson (2000; 2022). The results demonstrate that approximately 85% of the FDH estimators yield a value of 1, indicating that the national technology adheres to a convex frontier. According to Chatzistamoulou et al., (2022), the learning grid area defined between the national and international technologies represents the degree of knowledge transfer for each school.

international scale. This approach allows a comprehensive analysis of efficiency within a broader technological framework. The technological gap shows us how close the country frontier is to the metafrontier and "measures" the opportunity cost of not employing the best available technology (Cordero et al., 2017; Chatzistamoulou et al., 2019 Bonasia et al., 2020). Smaller values of the technology gap indicate smaller differences in the distance between the country frontier and the metafrontier, resulting in fewer efficiency losses. Conversely, higher values of this ratio are associated with greater disparities between the distances of the two frontiers, leading to larger efficiency losses. Additionally, the technology gap ratio reveals the degree of technological spillovers diffused towards the country technologies, with higher values indicating a smaller degree of such spillovers.

## 4.2 Technology gap determinants

The influence of different technologies on the effectiveness of schools goes beyond the boundaries of education production functions specific to individual countries. Embracing innovative educational technologies allows students and secondary schools to tap into a wide range of knowledge sources, thus promoting the development of unique pools of knowledge. Additionally, the ease of accessing and acquiring information from diverse channels enables the transfer of knowledge from advanced and highly efficient entities to those that are further behind the cutting edge. By adopting a hierarchical production structure, we are able to examine possible factors affecting schools' technology gap. To this end we employ the following relationship:

$$TG_i(x, y) = \alpha + \beta W_{1i} + e_i \tag{6}$$

where $\alpha$ is the constant term, $e_i$ is the statistical noise and $W_{1i}$ the vector of specific variables for each school. In this analysis, we adhere closely to the methodology put forth by Simar and Wilson (2007) for estimating the factors that impact the efficiency of each school unit. Specifically, we adopt the approach advocated by Simar and Wilson, which discourages the use of a Tobit estimator as an unsuitable econometric technique. Instead, we employ a truncated regression with bootstrap, incorporating a series of Monte Carlo experiments. This methodology allows us to examine and understand the factors influencing school unit efficiency more effectively. The existing literature has highlighted the issue of separability in two-stage DEA models (Daraio et al., 2018). Considering this concern, we conducted a similar test to assess the strength of the separability hypothesis, which unfortunately led to significant drawbacks in the results of our analysis (Emrouznejad and Yang, 2017; Daraio et al., 2018). This indicates that the separability problem had an impact on our findings, as suggested by previous research[3].

## 5 Data and Variables

This study uses data from the 2018 edition of the Programme for International Student Assessment (PISA)[4] (OECD, 2019). PISA measures student performance in three subjects, namely reading, mathematics and science, but also collects information about other aspects such as the background of students and teachers and the school environment. This information is drawn from questionnaires submitted by students, teachers, parents and school managers. Although each wave of PISA focuses on a main domain (reading, mathematics, science), all waves contain values for all the domains for the participant students (Wößmann, 2003). Table 1 presents the number of schools examined for our study by country.

To examine school level efficiency for a dataset of 34 OECD countries, using an educational production function, we aggregate all the dataset at school level[5] following the procedure of similar studies in that field (Agasisti and Zodio, 2015; 2019). To estimate the productive efficiency of each OECD country's specific frontier and the international metafrontier, we adopt a multi-output multi-input approach in line with the existing literature. In terms of outputs, we utilize student test scores in various key domains as a measure. Hence, we use ($PVIMATH$), ($PVIREAD$) and ($PVISCIE$) (see indicatively Agasisti and Zodio, 2015; 2019).

On the input side, we incorporate three variables as inputs. Firstly, we consider the inverse of the student-teacher ratio ($STRAT$)[6], which reflects the number of teachers per student and provides insights into the available human resources in schools. This variable allows us to assess the school's capacity in terms of teaching staff (Agasisti and Zodio, 2015; Aparicio et al., 2019; Cordero et al., 2018; 2020). Additionally, we utilize the inverse of the educational material shortage index ($EDUSH$) to measure the quality of educational resources and school infrastructures[7] (Aparicio et

[3] As there is no available software package specifically designed for conducting the test suggested by Daraio et al., (2018), we employed the Kolmogorov Smirnov test as an alternative, which can be regarded as a non-parametric substitute for the t-test (Mergoni and De Witte, 2022). This test allows us to evaluate whether the robust and conditional scores exhibit significantly different distributions. If the distributions of the robust and conditional scores are similar, it implies that the separability condition holds; otherwise, it suggests the contrary. Based on our findings, we have evidence to support the rejection of the null hypothesis.

[4] PISA, which was initiated in the late 1990s, is an ongoing international study conducted every three years. It involves the participation of students between the ages of 15 and 16 and focuses on assessing specific characteristics and skills.

[5] We need to mention that in order to have a more accurate and efficient aggregation of the data we use students' weights (the related variable name in PISA is W_FSTUWT).

[6] High values appear for Mexico and Colombia and low for Slovenia and Poland.

[7] This index contains data about the quality of the buildings such as lack of heating

al., 2019; Cordero et al., 2020). Finally, we proceed with the index of Economic, Social and Cultural Status (*ESCS*) which contains information about student background, parent's highest level of occupation and educational resources, along with infrastructures that are available at home (Agasisti and Zodio, 2015; 2019; Aparicio et al., 2019; Cordero et al., 2018; 2020). Note that the variables of (*EDUSH*) and (*ESCS*) may have negative values because, by construction, the averages of those indexes are equal to zero, so they need to be re-scaled in order to present positive values. The re-scaling process does not alter the DEA efficiency scores and has been adopted by previous studies (Aparicio et al., 2019; Cordero et al., 2020). Excluding missing values of inputs and outputs we end up with a sample of 8825 schools in 34 OECD countries. Table 2 displays the descriptive statistics of outputs and inputs by country for the schools included in the sample. Countries such as Japan, Korea, Estonia and Denmark exhibit high scores in terms of student performance in mathematics, science and reading. In contrast, countries like Colombia, Mexico, Turkey and Chile demonstrate lower student results in the same subject areas.

In the second stage of our analysis we argue that productive performance results at national and international level might be determined by i) student characteristics, ii) school attributes and iii) school practices and processes (see indicatively, Giambona et al., 2011; Agasisti and Zodio, 2015; 2019; Cordero et al., 2020; De Witte and Lopez-Torres, 2017, Deutch et al., 2019). Thus, in the first group we incorporate the age of the student (*AGE*) (Mancebón et al., 2012); the proportion of female students (*SEX*) at school (Perelman and Santin, 2011; Agasisti and Zodio, 2015;2019); the proportion of first generation immigrant students (*IMMIG*) (Agasisti and Zodio, 2018); the proportion of students that have repeated a class (*REPEAT*) (Agasisti and Zodio, 2015; 2019; Cordero et al., 2020; Delprato and Antequera, 2021) and the proportion of students that have missed at least one day at school (*STACCURACY*) in the last two weeks (Agasisti and Zodio, 2015; Delprato and Antequera, 2021). Moreover, we used the standard deviation of students' ESCS (*ESCSD*) to capture the differences of the student population within the school (Agasisti and Zodio, 2015; 2019) and the homework hours set by teachers per week (*HOMEWORK*) (Agasisti and Zodio, 2018).

The second group of variables affecting the technology gap also contains variables such as school area (*RURAL*) which is a dummy variable equal to 1 if the school is located in a village and 0 anywhere else (Perelman and Santin, 2011; Cordero et al., 2020; Delprato and Antequera, 2021); a dummy variable equal to 1 if the school ownership

and adequate space and shortage of infrastructure such as lack of computers, labs, internet connection, libraries, calculators, etc.

status is private ($PRIV$) and equal to 0 if it is not (Perelman and Santin, 2011; Agasisti and Zodio, 2019; Cordero et al., 2020); a dummy variable for school orientation ($ORIENT$) equal to 1 if the school's orientation is general and 0 if it is vocational or technical (Agasisti and Zodio, 2019); a dummy variable for the number of students in the class ($CLASSIZE$) equal to 1 if the class has less than 20 students or 0 if the class has more than 20 (Perelman and Santin, 2011; Cordero et al., 2020) and school size ($SCHSIZE$) which is the total number of students in the school (Perelman and Santin, 2011; Cordero et al., 2018; 2020).

Lastly, the third group comprises variables related to school practices and processes. Two indicators are intended to capture school funding from the government ($FUND1$) and individuals ($FUND2$) (Agasisti and zodio, 2012) and the proportion of certified teachers ($CERT$) (Agasisti and Zodio, 2018). Additionally, we include a binary dummy variable, denoted as ($ACCOUNT$) which takes a value of 1 if achievement data are publicly posted and 0 otherwise (Agasisti and Zodio, 2019); a dummy variable equal to 1 if there is a quality assurance system that includes external evaluations at school ($EXTEVAL$) and 0 if not (Agasisti and Zodio, 2015); a dummy variable equal to 1 if learning is hindered by students lacking respect for teachers ($POORREL$) and 0 otherwise (Agasisti and Zodio, 2015); a dummy variable which takes the value 1 if the school competes with one or more schools for students ($COMPET$) and 0 if not (Agasisti and Zodio, 2015; 2019); and the perception of competitiveness conceived by principals ($PERCOMP$) (Agasisti and Zodio, 2018); a variable that measures the discipline climate ($DISCCLIMATE$) in test language lessons (Perelman and Santin, 2011; Cordero et al., 2018) with higher values of this index meaning a more disciplined class and, finally, an index that measures the number of extra curriculum activities ($EXTCURRA$) provided by the school (Agasisti and Zodio, 2019)[8]. Table 3 provides descriptive statistics for all the variables examined in the second stage of our analysis.

## 6 Results & Discussion

### 6.1 Efficiency, meta-efficiency scores and technology gaps

Table 4 presents a summary of various metrics, including the DEA scores, bootstrapped DEA scores, bias, and confidence intervals, categorized by country. These metrics are calculated based on the available sample of schools. The results are divided into national (frontier) technology and international (meta) technology, and the last column displays the corresponding technology gaps. The specific measures were estimated using the bootstrap DEA[9]. Hence, the estimated bootstrapped efficiency

[8] Table 2 in the Appendix A provides a detailed description of the variables used.

[9] To this end we employ SIMARWILSON, the Stata module to perform Simar and Wilson (2007) efficiency analysis (Badunenko and Tauchman, 2019). We also test

scores for each school capture two aspects. Firstly, they reflect the change in distance from the national frontier, indicating how close or far each school is from the best performance within their respective country. Secondly, the scores also capture the movement of each school, indicating whether they have improved or declined over time (Tsekouras et al., 2016).

Compared to previous studies utilizing previous PISA evaluations, our findings show that the average efficiency with respect to the national technology frontier is significantly higher at 0.866 (Agasisti and Zoido, 2019). However, when considering the average bootstrapped DEA estimates related to the international metafrontier, which is at 0.735, there is still significant room for improvement. Notably, Finland, Ireland, Iceland and New Zealand (Bogetoft et al., 2015) demonstrate high technical efficiency and can be considered leading performers, achieving average TE scores close to 92% with minimal variation. Conversely, Lithuania and Poland exhibit poorer performance in the 2018 PISA evaluation, as illustrated in Figure 1 of Appendix B. Australia falls into the group of countries with lower performance. The boxplots visually represent the efficiency scores, showing that some countries have very few outliers, while others, such as Australia, Denmark, Spain, Poland, Portugal and Sweden, have schools with both exceptionally high and low efficiency performance.

Upon closer examination of the relationship between national technical efficiency and mathematics and reading performance, a significant correlation becomes apparent (Fig. 2). On the vertical axis, there are the country averages of mathematics (Fig.2a) and reading (Fig.2b) test scores while on the horizontal axis there are the average bootstrapped efficiency scores obtained through the national frontier. Both variables in the vertical and horizontal axis have been aggregated at the country level for this illustration. The results indicate a positive relationship between the bootstrap efficiency scores and the reading-mathematics test scores (Agasisti and Zoido, 2019). However, countries such as Colombia, Mexico, Turkey and Chile do not confirm this relationship.

Turning now to the international frontier we estimate bootstrap technical efficiency scores under the assumption that all countries have access to a common international metatechnology (Tsekouras et al., 2016; 2017). Under this perspective, Japan, South Korea, Estonia, Poland and the United States are the leading countries defining the metatechnology. In contrast, compared with the other OECD countries, the group of laggards, namely Iceland, Israel, Slovakia and Greece, achieve lower efficiency scores (Cordero et al., 2017; 2020), suggesting that knowledge spillover effects are not in operation within country-specific technologies (see also Figure 2 in Appendix B). However, it is crucial to note that the results regarding international technology are characterized by very low

whether the separability condition described by Simar and Wilson (2007) is satisfied.

dispersion and thus no significant deviations between the examined countries exist.

The results obtained for international technology are in accordance with findings from individual countries and groups using alternative approaches (i.e. Aparicio et al., 2018; Cordero et al., 2017; 2020; Agasisti and Zoido, 2019). Table 5 provides a more comprehensive analysis of the most and least inefficient schools in each country under metatechnology. Panel A includes the efficient schools, which are schools with efficiency scores above the 90th percentile, while Panel B consists of the inefficient schools with scores below the 10th percentile. Additionally, column (i) calculates the percentage of efficient schools in each country (Panel A) or inefficient schools (Panel B), while column (j) represents the proportion of each country's schools in the group with the most or least efficient ones. Upon closer examination, it becomes evident that the efficient schools, on average, exhibit higher performance in reading, mathematics and science compared to the least efficient schools. This finding reaffirms the positive relationship between efficiency scores and test scores as previously described (Fig. 3a and 3b). However, it is worth noting that while most schools belonging to the most efficient group surpass the OECD average in all three domains, there are countries where efficient schools exist despite their average test scores being below the OECD averages. For instance, Mexico has 47 schools classified as most efficient. This may be explained by the fact that ($EDUSHORT$) is above average although ($STRATIO$) is really high (there are 45 students per teacher) and ($ESCS$) of students is far below the average of the most efficient schools (lower ($ESCS$) denotes that students have low levels of socioeconomic background which leads to lower levels of performance). Therefore, even if the 47 Mexican schools have lower averages in two out of three inputs used in the analysis they are making the most of their available resources and fall within the most efficient of the sample.

Similar results can be found in Panel B which contains the most inefficient schools: A significant number of Israeli schools are included in the most inefficient category despite the fact that ($STRATIO$) and ($EDUSHORT$) are higher than the averages compared with the values that most efficient schools have in those indexes. Another example arises with the three inefficient schools of Japan. Their average test scores are not as low as those of other inefficient schools, but in order to achieve them, they use a large amount of resources i.e. many teachers and more educational material.

Further valuable insights can be gained from analyzing the percentages of the most and least efficient schools in each country, as well as the contribution of each country to the efficiency frontier. In Panel A, Germany stands out with 48 out of 177 schools classified as the most efficient, indicating that over 27% of German schools are considered efficient. Notable mentions include Turkey, where 26.63% of schools are categorized as efficient, and the Netherlands, with 25% of schools falling into this category. However, the contribution to the efficiency frontier varies. Specifically, schools in the Czech Republic make up 9% of the group of efficient schools, while Estonian schools account for 6.37% of that group. In Panel B, one-third of schools in Israel are classified as inefficient, highlighting a significant proportion. Slovakia follows with 26.36% of its schools falling into the inefficient category, closely followed by Hungary, with 25.58% of schools considered inefficient. Additionally, Slovakian and Lithuanian schools together make up 20.86% of the group of inefficient schools, with each country representing 10.43% respectively. Interestingly, Ireland does not have a single inefficient school, indicating a high level of efficiency within its education system. Conversely, Estonia has two inefficient schools, while the United States has three.

In addition to the findings related to the bootstrap efficiency scores in terms of national and international technology, it is intriguing to explore the results regarding the technology gap. The technology gap calculated in this study illustrates the proximity of a country's technology to the international meta-technology, focusing on the improvement of performance in reading, science and mathematics across schools. By examining the technology gap, we can assess potential incoming spillovers and evaluate a country's absorptive capabilities in assimilating and utilizing existing knowledge within their educational production process. Therefore, the technology gap serves as a valuable tool for policymakers, offering additional insights into the potential benefits of various policies and programmes. This information can guide decision-makers in identifying strategies that could yield favourable outcomes (Battesse et al., 2004; O'Donnell, 2008).

Figure 3 displays the distribution of productive efficiency scores concerning national and international technology, as well as technology gaps. It is evident that at the national level, schools demonstrate lower productive performance and exhibit less variability within the group compared to the international context. Notably, the meta-technology scores exhibit a bimodal distribution pattern, highlighting interesting variations. Moreover, based on the data in Table 4, it can be deduced that Poland, Australia, Estonia and Lithuania have minimal technology gaps. Conversely, Luxembourg, Iceland and Israel have notably lower metatechnology ratios, indicating significant differences in their technological levels. For a visual representation of the distribution of technology gaps, please refer to Figure 4.

## 6.2 Determinants of school technology gaps

After estimating school efficiency at the national and international levels, we proceed to analyze the potential factors that affect the technology gap. The concept of technology gap, as utilized in the second stage of our analysis, allows us to examine the productivity differences among the schools under investigation. In this analysis, we employ a range of covariates to explore the factors that contribute to variations in the technology gap. These variables fall into three distinct groups: student features, school attributes, and school practices and processes. Previous studies by Agasisti and Zoido (2018, 2019), Cordero et al., (2020), and De Witte and Lopez-Torres (2017) inform the selection of these explanatory variables. To account for structural differences across countries, our estimates include country-level fixed effects. This approach ensures that the analysis considers the unique characteristics and contextual factors associated with each country.

Table 6 displays the value of each estimated coefficient, the t-statistic and the corresponding p-value for the second estimation stage , through the robust, double bootstrap method provided by Simar and Wilson (2007)[10]. The first group of variables that influence the school technology gap demonstrates a significant statistical impact. This observation suggests that these variables play a crucial role in narrowing this gap. More specifically, the (*SEX*) variable negatively affects the technology gap, revealing that a higher proportion of female students reduces the gap (Agasisti and Zodio, 2019) while the variable related to the proportion of immigrant students (*IMMIG*) seems to have no effect. A negative relationship has been detected for the (*AGE*) variable (Cordero et al., 2018). In contrast, the (*ESCSDS*) variable is positively associated with the technology gap. The specific finding pertains to the impact of students' diverse socio-economic backgrounds on the technology gap. This finding can be attributed to the dispersion of student characteristics, leading to the formation of heterogeneous groups within schools. This raises the question of potentially creating more focused and homogeneous groups as a strategy (Agasisti and Zodio, 2020). Additionally, two other variables, (*REPEAT*) and (*STACCURACY*), are found to widen the performance gap between schools (Agasisti and Zodio, 2019; Cordero et al., 2020). These results are particularly significant as they underscore the importance of developing a roadmap to address the needs of students with unique characteristics and low achievement behaviour (Aparicio et al., 2020). Lastly, the negative effect of the (*HOMEWORK*) variable indicates the significant role of homework hours assigned by teachers per week in reducing inequality in

[10] Changing the number of replications involves no significant variations in the estimated variables. Moreover, examining the variables for each group separately does not entail changes in the statistical significance of our variables.

school performance (Agasisti and Zodio, 2018). This finding highlights the importance of homework as a tool for mitigating performance disparities among students.

Turning our attention to school-specific factors, we find that schools located in non-urban areas (*RURAL*) do not show a statistically significant effect on the technology gap (Aparicio et al., 2018; Cordero et al., 2020). This finding indicates that schools in urban areas, despite potential advantages such as better organization, infrastructure and additional support structures, do not possess a comparative advantage in reducing the technology gap. Furthermore, our empirical findings reveal a negative effect of the (*PRIV*) variable on the technology gap (Cordero et al., 2018). This result aligns with a significant body of literature suggesting that students attending private schools tend to perform better in terms of mathematics, reading and science (Agasisti and Zodio, 2018; 2019). Lastly, the orientation of schools (*ORIENT*) exhibits a statistically significant and negative effect. This means that schools with a general academic orientation make a significant contribution to reducing the technology gap among the schools examined (Agasisti and Zodio, 2018).

Turning our attention to two significant variables in the literature, namely classroom size and school size (*CLASSSIZE*) and (*SCHSIZE*), we observe that they have distinct effects. Smaller class sizes are negatively associated with the school's technology gap. Specifically, classes with fewer than twenty students operate efficiently, thereby reducing the technology gap in the dataset analyzed using PISA 2018. One possible explanation for this finding lies in the additional level of resources allocated to these smaller classes, as noted in prior studies (Santin and Sicilia, 2012; Cordero et al., 2018; Agasisti and Zodio, 2019). On the other hand, school size (*SCHSIZE*) has a small negative effect, and our estimates do not support the existence of quadratic effects. Our empirical results align with various studies that link inefficiencies in large schools to significant diseconomies of scale (Alexander et al., 2010).

Our analysis now shifts towards the third group of variables. As anticipated, the pressures stemming from neighbouring schools in terms of competition (*COMPET*) have a negative effect on the technology gap. This reduction can be attributed to schools' efforts to enhance their performance and become more competitive within their operating area (Aparicio et al., 2018; Agasisti and Zodio, 2018; 2019). A similar behaviour is observed for the (*PERCOMP*) variable, which represents the perceived level of competition by each school principal. Furthermore, the proportion of certified teachers (*CERT*) is found to reduce the technology gap, indicating that the qualification status of teachers plays a significant role in the educational production process (Agasisti and Zodio, 2018).

The empirical results regarding the influence of external evaluation (*EXTEVAL*) are quite interesting. The negative sign reinforces the view that conducting evaluation in schools with external judges improves their performance and reduces the technology gap. In addition, as expected, the variable (*POORREL*) shows a positive sign while ($ACCOUNT$) a negative one. Hence, non-positive relations between teacher and students (Agasisti and Zodio, 2018) increase the relative distance from the frontier, while the decision to publish and post a school's achievements, awards and other practices reduce the distance. Similarly, extra-curricular activities (*EXTRACURRA*) reduce the technology gap.

No significant effects on the level of the technology gap within each school are observed for the variable ($FUND1$), which represents the proportion of funding from governmental sources. However, a negative influence is detected for ($FUND2$), which signifies the role of additional funding sources such as fees, donations, and charges. This suggests that investment in education from these supplementary sources may contribute to reducing the technology gap by improving infrastructure, minimizing wastage and enhancing completion rates (Jimenez and Paqueo, 1996) It is worth noting that although several other variables were included as explanatory factors, they were found to be statistically insignificant, and their inclusion led to a decline in the performance of our model.

## 7 Concluding remarks

The productive performance of schools relies not only on the quality and efficiency of the national educational system, but also to some extent on international educational technologies. The disparity between national technology and the cutting-edge frontier technology explains a significant portion of the observed differences across countries. By connecting the concept of technology gap to our empirical findings, we expanded the current understanding of why school performance, as measured by the latest PISA variables, varies between national and international technology contexts. It is imperative for policymakers and governments to carefully consider the factors that facilitate or hinder the existence of substantial technological gaps. This becomes crucial in a modern world where education transcends national boundaries and takes on global dimensions through knowledge transfer and spillover effects.

The existing literature assumes a uniformity of technology among the schools being examined. As a result, estimates are made using a common benchmark (meta-technology) while disregarding national technologies (Burger et al., 2022). The presence of technology heterogeneity (Tsekouras et al., 2017) in the school benchmarking process distorts estimates and can lead to misleading policy measures. In this study, we adopted a non-parametric frontier approach in two stages to examine the productive performance of 8825 schools under both their national and international technology contexts.

The empirical results indicate that, on average, most countries achieve high performance with respect to their national technology. Countries such as Finland, Ireland, Iceland and New Zealand are listed as the champions, while Lithuania and Poland lag behind. Moreover, Germany, the Netherlands and Turkey exhibit an interesting behaviour with a significant percentage of top-performing schools. In terms of international technology, Japan, South Korea, Estonia, Poland and the USA dominate, while Iceland, Slovakia and Greece underperform, revealing a completely different landscape. In this case, the average scores are significantly lower, highlighting ample room for improvement. Additionally, the study reveals significant technology gaps, emphasizing the missed opportunities of not utilizing the best available technology. Implementing annual national monitoring analyses independent of PISA evaluations can be an effective policy intervention to reduce technology gaps and help countries catch up. Such a policy would enable countries with higher performance technology gaps to conduct their own national monitoring studies, compare their results with international research, and develop their own innovative capabilities for improving school performance while benefiting from existing spillover effects.

In the second stage of our analysis, we adopted the approach of Simar and Wilson (1998), which provides robust evidence of the impact on countries' technology gaps. Consistent with the existing literature on the determinants of school technical efficiency scores, we considered the effects of contextual variables belonging to three broad categories. Our results indicate a favourable effect on reducing the technology gap for some variables, while others have a positive impact that tends to widen significant technological gaps. Educational policymakers should focus on expanding the provision of remedial classes for at-risk students and making targeted homework assignments for teachers more meaningful. It is also crucial to improve access to qualified teachers for disadvantaged students and provide specific facilities for schools in rural areas. From a policy perspective, the role of competition in school performance should be emphasized. Addressing technology gaps necessitates policies aimed at optimizing resource allocation for achieving higher academic results. Additionally, policies to address poor relationships within schools can reduce inefficiency, but their effectiveness depends on the level and quality of teachers involved. Replacing uncertified and less qualified teachers with those who are certified and highly qualified enhances efficiency, whereas policies that involve combining classes or substituting non-relief teachers hinder efficiency.

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## A Appendix

Table 1: Number of schools examined by country

| **Country** | **Schools** | **Country** | **Schools** |
|---|---|---|---|
| Australia | 609 | Latvia | 290 |
| Belgium | 236 | Lithuania | 361 |
| Chile | 202 | Luxembourg | 58 |
| Colombia | 240 | Mexico | 280 |
| Czech Republic | 321 | Netherlands | 136 |
| Denmark | 254 | New Zealand | 179 |
| Estonia | 229 | Poland | 240 |
| Finland | 194 | Portugal | 242 |
| France | 197 | Slovakia | 344 |
| Germany | 177 | Slovenia | 314 |
| Greece | 227 | South Korea | 187 |
| Hungary | 215 | Spain | 959 |
| Iceland | 125 | Sweden | 194 |
| Ireland | 146 | Switzerland | 217 |
| Israel | 154 | Turkey | 184 |
| Italy | 469 | United Kingdom | 328 |
| Japan | 183 | United States | 134 |
| **Total** | | | **8825** |

Table 2: Descriptive statistics of inputs and outputs by country

| Panel A: Outputs | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variables | | | PV1MATH | | | | | | PV1READ | | PV1SCIE | | Country |
| **Obs** | **Mean** | **Sd** | **Min** | **Max** | **Mean** | **Sd** | **Min** | **Max** | **Mean** | **Sd** | **Min** | Max | |
| AUS | 609 | 489.60 | 49.54 | 298.84 | 707.69 | 500.88 | 52.71 | 278.41 | 681.75 | 500.82 | 50.35 | 303.94 | 711.40 |
| BEL | 236 | 504.15 | 69.15 | 312.83 | 633.39 | 489.85 | 71.72 | 232.75 | 624.83 | 497.12 | 70.07 | 318.52 | 631.96 |
| CHE | 217 | 513.00 | 57.06 | 306.50 | 655.95 | 479.79 | 64.77 | 273.11 | 623.98 | 491.27 | 59.73 | 315.38 | 628.56 |
| CHL | 202 | 421.87 | 65.99 | 110.69 | 550.84 | 458.13 | 70.11 | 146.71 | 574.80 | 448.29 | 64.80 | 223.35 | 574.79 |
| COL | 240 | 393.27 | 54.08 | 262.68 | 540.49 | 413.06 | 61.99 | 225.84 | 587.93 | 414.72 | 56.29 | 267.54 | 566.54 |
| CZE | 321 | 502.46 | 69.39 | 334.48 | 646.11 | 493.97 | 74.68 | 299.87 | 643.90 | 501.07 | 72.95 | 323.43 | 664.37 |
| DEU | 177 | 494.74 | 70.31 | 319.05 | 626.02 | 493.79 | 78.82 | 317.59 | 633.04 | 495.82 | 76.41 | 294.00 | 638.05 |
| DNK | 254 | 499.55 | 42.02 | 375.72 | 695.01 | 491.73 | 46.22 | 340.20 | 704.07 | 482.16 | 44.04 | 321.09 | 608.37 |
| ESP | 959 | 486.23 | 38.05 | 336.40 | 602.36 | 478.52 | 41.69 | 270.15 | 610.66 | 486.58 | 37.04 | 312.95 | 587.93 |
| EST | 229 | 520.93 | 45.32 | 411.89 | 709.87 | 521.79 | 50.56 | 398.00 | 724.72 | 527.57 | 49.41 | 383.16 | 752.37 |
| FIN | 194 | 504.55 | 39.23 | 302.97 | 627.98 | 517.80 | 47.11 | 271.90 | 701.03 | 517.20 | 40.62 | 311.25 | 647.85 |
| FRA | 197 | 481.87 | 72.43 | 265.90 | 622.60 | 478.73 | 75.63 | 293.62 | 628.02 | 479.89 | 72.20 | 298.63 | 618.31 |
| GBR | 328 | 499.01 | 43.45 | 383.97 | 615.58 | 503.05 | 45.03 | 381.43 | 631.87 | 496.96 | 45.78 | 383.02 | 640.07 |
| GRC | 227 | 440.57 | 59.28 | 219.94 | 608.90 | 445.56 | 70.76 | 163.28 | 623.47 | 442.84 | 58.79 | 267.63 | 611.82 |
| HUN | 215 | 461.67 | 75.97 | 240.28 | 630.57 | 456.95 | 78.97 | 290.51 | 637.33 | 460.79 | 77.55 | 287.82 | 655.24 |
| IRL | 146 | 497.91 | 33.44 | 391.14 | 577.69 | 517.19 | 37.69 | 385.80 | 608.45 | 494.51 | 35.89 | 356.30 | 601.96 |
| ISL | 125 | 490.20 | 36.38 | 305.15 | 571.56 | 469.83 | 38.41 | 343.86 | 573.48 | 469.01 | 36.41 | 347.62 | 558.63 |
| ISR | 154 | 454.35 | 76.16 | 238.47 | 585.08 | 460.97 | 91.74 | 192.68 | 592.62 | 454.84 | 80.35 | 250.88 | 583.37 |
| ITA | 469 | 481.84 | 67.59 | 245.68 | 631.02 | 466.26 | 69.61 | 240.43 | 607.82 | 462.75 | 63.98 | 216.01 | 601.45 |
| JPN | 183 | 526.86 | 58.57 | 401.17 | 665.78 | 501.75 | 62.71 | 369.09 | 638.53 | 527.89 | 59.73 | 416.86 | 664.20 |
| KOR | 187 | 523.42 | 57.19 | 372.35 | 729.81 | 513.04 | 55.09 | 354.41 | 678.31 | 519.07 | 53.81 | 360.32 | 692.90 |
| LTU | 361 | 461.91 | 62.47 | 278.04 | 672.67 | 449.08 | 68.78 | 229.38 | 654.50 | 458.38 | 62.58 | 279.14 | 657.61 |
| LUX | 58 | 485.78 | 56.92 | 393.65 | 597.66 | 471.80 | 61.94 | 371.11 | 584.93 | 481.66 | 59.31 | 392.87 | 582.56 |
| LVA | 290 | 487.34 | 43.13 | 306.39 | 650.04 | 466.28 | 48.90 | 286.56 | 585.46 | 478.06 | 43.53 | 337.72 | 597.00 |
| MEX | 280 | 404.34 | 49.80 | 245.95 | 540.56 | 416.52 | 56.07 | 236.46 | 580.82 | 413.26 | 48.74 | 268.97 | 564.32 |
| NLD | 136 | 519.89 | 70.44 | 347.39 | 648.91 | 483.98 | 76.87 | 307.49 | 632.11 | 503.08 | 77.85 | 312.30 | 645.64 |
| NZL | 179 | 491.56 | 42.53 | 378.15 | 596.34 | 506.22 | 47.08 | 369.25 | 620.20 | 508.86 | 46.70 | 372.08 | 629.69 |
| POL | 240 | 518.34 | 50.59 | 309.75 | 708.81 | 513.89 | 53.97 | 294.54 | 698.67 | 511.67 | 52.49 | 268.92 | 689.47 |
| PRT | 242 | 481.57 | 58.20 | 280.35 | 598.27 | 480.03 | 60.08 | 257.02 | 596.12 | 480.91 | 54.47 | 325.35 | 593.36 |
| SVK | 349 | 474.58 | 67.97 | 243.66 | 664.15 | 442.00 | 72.01 | 225.21 | 624.20 | 451.77 | 65.42 | 261.03 | 615.41 |
| SVN | 314 | 477.70 | 69.46 | 277.24 | 662.10 | 465.02 | 71.15 | 252.04 | 641.68 | 475.43 | 69.92 | 288.48 | 627.66 |
| SWE | 194 | 507.25 | 46.33 | 370.59 | 636.75 | 513.06 | 54.36 | 324.75 | 695.81 | 505.34 | 50.55 | 337.49 | 675.14 |
| TUR | 184 | 447.61 | 68.73 | 276.86 | 659.86 | 459.39 | 68.29 | 308.62 | 643.84 | 462.23 | 65.25 | 304.96 | 639.40 |
| USA | 134 | 474.32 | 46.80 | 266.99 | 579.73 | 501.89 | 51.97 | 267.03 | 619.82 | 498.78 | 47.06 | 323.26 | 609.84 |
| **Sample** | **8825** | **482.26** | **63.80** | **110.69** | **729.81** | **478.53** | **66.47** | **146.71** | **724.72** | **481.30** | **63.08** | **216.01** | **752.37** |

| Panel B: Inputs | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variables | | | STRATIO | | | | EDUSHORT | | | | ESCS | | |
| Country | Obs | Mean | Sd | Min | Max | Mean | Sd | Min | Max | Mean | Sd | Min | Max |
| AUS | 609 | 13.20 | 4.47 | 4.14 | 100.00 | 0.948 | 0.905 | 0.01 | 4.39 | 4.392 | 0.496 | 2.565 | 5.668 |
| BEL | 236 | 9.01 | 3.17 | 1.74 | 23.71 | 1.371 | 0.888 | 0.01 | 4.39 | 4.145 | 0.508 | 2.765 | 5.212 |
| CHE | 217 | 12.19 | 7.58 | 3.65 | 100.00 | 0.956 | 0.841 | 0.01 | 3.62 | 4.084 | 0.495 | 2.213 | 5.449 |
| CHL | 202 | 18.78 | 9.66 | 2.74 | 100.00 | 1.148 | 0.882 | 0.01 | 4.39 | 3.684 | 0.887 | 0.572 | 5.408 |
| COL | 240 | 24.37 | 11.57 | 1.00 | 100.00 | 2.093 | 1.219 | 0.01 | 4.39 | 2.907 | 0.959 | 0.007 | 5.303 |
| CZE | 321 | 12.70 | 3.49 | 2.76 | 22.92 | 1.588 | 0.792 | 0.01 | 4.39 | 3.920 | 0.540 | 2.279 | 5.159 |
| DEU | 177 | 13.93 | 4.12 | 2.48 | 37.36 | 1.687 | 0.976 | 0.01 | 4.39 | 3.916 | 0.607 | 2.367 | 5.186 |
| DNK | 254 | 12.93 | 6.49 | 1.19 | 100.00 | 1.041 | 0.856 | 0.01 | 4.39 | 4.475 | 0.421 | 2.946 | 5.349 |
| ESP | 959 | 11.68 | 4.74 | 1.00 | 51.58 | 1.543 | 1.070 | 0.01 | 4.39 | 3.992 | 0.556 | 2.195 | 5.539 |
| EST | 229 | 11.29 | 3.58 | 2.60 | 21.51 | 1.542 | 0.842 | 0.01 | 4.39 | 4.085 | 0.456 | 2.925 | 5.473 |
| FIN | 194 | 10.89 | 2.33 | 3.85 | 19.49 | 1.524 | 0.818 | 0.01 | 3.62 | 4.357 | 0.362 | 2.651 | 5.618 |
| FRA | 197 | 11.79 | 3.20 | 1.00 | 31.33 | 1.175 | 0.956 | 0.01 | 4.39 | 3.950 | 0.550 | 2.046 | 5.113 |
| GBR | 328 | 15.23 | 3.36 | 1.25 | 25.19 | 1.482 | 1.025 | 0.01 | 4.39 | 4.341 | 0.422 | 3.387 | 5.616 |
| GRC | 227 | 9.32 | 2.84 | 2.15 | 24.17 | 2.031 | 1.038 | 0.01 | 4.39 | 3.846 | 0.617 | 1.354 | 5.367 |
| HUN | 215 | 10.35 | 4.97 | 1.79 | 69.00 | 1.821 | 0.958 | 0.01 | 4.39 | 3.804 | 0.734 | 1.503 | 5.319 |
| IRL | 146 | 12.68 | 2.18 | 3.49 | 17.37 | 1.598 | 1.028 | 0.01 | 4.39 | 4.202 | 0.390 | 3.152 | 5.148 |
| ISL | 125 | 9.02 | 2.63 | 1.18 | 14.33 | 1.094 | 0.849 | 0.01 | 2.90 | 4.458 | 0.396 | 3.192 | 5.110 |
| ISR | 154 | 11.27 | 10.57 | 1.00 | 100.00 | 1.793 | 1.058 | 0.01 | 4.39 | 4.400 | 0.562 | 2.342 | 6.351 |
| ITA | 469 | 8.61 | 6.82 | 1.19 | 100.00 | 1.677 | 0.956 | 0.01 | 4.39 | 3.800 | 0.493 | 1.374 | 5.115 |
| JPN | 183 | 11.95 | 4.73 | 1.00 | 31.03 | 2.173 | 0.914 | 0.01 | 4.39 | 3.983 | 0.371 | 3.211 | 4.924 |
| KOR | 187 | 13.09 | 3.82 | 1.00 | 27.35 | 1.853 | 0.936 | 0.01 | 4.39 | 4.163 | 0.389 | 3.026 | 5.111 |
| LTU | 361 | 9.44 | 3.43 | 1.56 | 33.73 | 1.505 | 0.744 | 0.01 | 4.39 | 3.964 | 0.549 | 2.472 | 5.489 |
| LUX | 58 | 8.89 | 1.95 | 3.80 | 12.42 | 1.067 | 0.778 | 0.13 | 2.97 | 4.216 | 0.645 | 3.258 | 5.427 |
| LVA | 290 | 10.17 | 6.21 | 1.00 | 100.00 | 1.274 | 0.804 | 0.01 | 3.62 | 3.955 | 0.483 | 2.014 | 5.225 |
| MEX | 280 | 31.47 | 19.10 | 2.33 | 100.00 | 1.958 | 1.268 | 0.01 | 4.39 | 2.886 | 0.936 | 0.547 | 5.346 |
| NLD | 136 | 17.13 | 5.75 | 4.84 | 60.13 | 0.996 | 0.845 | 0.01 | 3.36 | 4.388 | 0.423 | 3.399 | 5.278 |
| NZL | 179 | 13.83 | 3.02 | 1.24 | 20.05 | 1.150 | 0.851 | 0.01 | 3.57 | 4.227 | 0.474 | 3.062 | 5.251 |
| POL | 240 | 7.98 | 3.07 | 1.00 | 16.57 | 1.269 | 0.895 | 0.01 | 4.39 | 3.948 | 0.466 | 2.447 | 5.272 |
| PRT | 242 | 9.86 | 4.42 | 1.00 | 50.62 | 1.933 | 0.977 | 0.01 | 4.39 | 3.662 | 0.604 | 2.277 | 5.213 |
| SVK | 349 | 12.78 | 6.85 | 3.57 | 100.00 | 1.849 | 0.882 | 0.01 | 4.39 | 3.779 | 0.654 | 1.177 | 5.136 |
| SVN | 314 | 7.39 | 4.82 | 1.00 | 35.00 | 1.371 | 0.907 | 0.01 | 4.39 | 3.979 | 0.513 | 1.152 | 5.166 |
| SWE | 194 | 11.63 | 3.58 | 2.50 | 23.17 | 0.926 | 0.896 | 0.01 | 3.89 | 4.467 | 0.397 | 3.384 | 5.496 |
| TUR | 184 | 13.46 | 4.40 | 2.34 | 40.76 | 0.908 | 0.919 | 0.01 | 3.56 | 2.912 | 0.754 | 0.546 | 5.200 |
| USA | 134 | 17.01 | 10.01 | 1.67 | 100.00 | 1.026 | 0.943 | 0.01 | 3.89 | 4.211 | 0.510 | 2.886 | 5.342 |
| **Sample** | **8825** | **12.67** | **7.85** | **1.00** | **100.00** | **1.472** | **1.008** | **0.01** | **4.39** | **3.970** | **0.685** | **0.007** | **6.351** |

Table 3: Descriptive statistics of second stage variables

| | | | | |
|---|---|---|---|---|
| **Student Features** | | | | |
| Variable | Mean (or %) | Sd | Min | Max |
| AGE | 15.78 | 0.118 | 15.25 | 16.33 |
| SEX | 0:0.511 % | 0.118 | 0.000 | 1.000 |
| | 1:0.489 % | | | |
| REREAT | 0:0.859 % | 0.105 | 0.000 | 1.000 |
| | 1:0.141 % | | | |
| HOMEWORK | | | | |
| IMMIG | 0:0.687 % | 0.381 | 0.000 | 1.000 |
| | 1:0.313 % | | | |
| ESCSSD | 0.788 | 0.205 | 0.026 | 2.803 |
| STACCURACY | 0:0.775 % | 0.202 | 0.000 | 1.000 |
| | 1:0.252 % | | | |
| **School Features** | | | | |
| RURAL | 0:0.876 % | 0.330 | 0.000 | 1.000 |
| | 1:0.124 % | | | |
| PRIV | 0:0.803 % | 0.398 | 0.000 | 1.000 |
| | 1:0.106 % | | | |
| ORIENT | 0.149 % | 0.358 | 0.000 | 1.000 |
| | 1:0.197 % | | | |
| CLASSSIZE | 0:0.722 % | 0.448 | 0.000 | 1.000 |
| | 1:0.278 % | | | |
| SCHSIZE | 692.56 | 593.229 | 5 | 8150 |
| **School Practices and Processes** | | | | |
| FUND1 | 0:0.382 % | 0.272 | 0.000 | 1.000 |
| | 1:0.618 % | | | |
| FUND2 | 0:0.271 % | 0.1325 | 0.000 | 1.000 |
| | 1:629 % | | | |
| CERT | 0:0.824 % | 0.325 | 0.000 | 1.000 |
| | 1:0.175 % | | | |
| ACCOUNT | 0.658 % | 0.474 | 0.000 | 1.000 |
| | 1:0.342 % | | | |
| EXTEVAL | 0.226 % | 0.418 | 0.000 | 1.000 |
| | 1:0.774 % | | | |
| POORREL | 0.973 % | 0.163 | 0.000 | 1.000 |
| | 1:0.027 % | | | |
| COMPET | 0.210 % | 0.407 | 0.000 | 1.000 |
| | 1:0.790 % | | | |
| PERCOMP | | | | |
| DISCCLIMATE | 0.008 | 1.088 | -2.712 | 2.035 |
| EXTRACURRA | 1.799 | 1.039 | 0 | 3 |
| | 0.851 % | | | |

## Table 4: Efficiency scores and technology gap, by country.

| Country | Country/National Frontier | | | | | Metafrontier/International Frontier | | | | | Technology gap |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | TE | TEBC | BIAS | TEBC LB | TEBC UB | TE | TEBC | BIAS | TEBC LB | TEBC UB | TG |
| | (a) | (b) | (c) | (d) | (e) | (f) | (g) | (h) | (i) | (j) | (k)=1-(g/b) |
| Australia | 0.834 | 0.799 | 0.035 | 0.779 | 0.821 | 0.756 | 0.739 | 0.017 | 0.731 | 0.748 | 0.074 |
| Belgium | 0.891 | 0.866 | 0.025 | 0.847 | 0.885 | 0.751 | 0.736 | 0.015 | 0.727 | 0.743 | 0.152 |
| Switzerland | 0.882 | 0.853 | 0.029 | 0.831 | 0.875 | 0.752 | 0.731 | 0.021 | 0.721 | 0.742 | 0.143 |
| Chile | 0.923 | 0.898 | 0.025 | 0.876 | 0.919 | 0.755 | 0.729 | 0.026 | 0.715 | 0.742 | 0.190 |
| Colombia | 0.871 | 0.839 | 0.032 | 0.817 | 0.863 | 0.776 | 0.731 | 0.046 | 0.711 | 0.752 | 0.128 |
| Czech Republic | 0.913 | 0.889 | 0.024 | 0.870 | 0.908 | 0.774 | 0.753 | 0.020 | 0.743 | 0.764 | 0.154 |
| Germany | 0.921 | 0.895 | 0.026 | 0.871 | 0.917 | 0.779 | 0.756 | 0.023 | 0.745 | 0.768 | 0.157 |
| Denmark | 0.876 | 0.843 | 0.033 | 0.821 | 0.867 | 0.739 | 0.721 | 0.018 | 0.712 | 0.730 | 0.143 |
| Spain | 0.907 | 0.888 | 0.019 | 0.877 | 0.901 | 0.752 | 0.732 | 0.019 | 0.722 | 0.742 | 0.176 |
| Estonia | 0.886 | 0.851 | 0.035 | 0.826 | 0.879 | 0.804 | 0.787 | 0.017 | 0.778 | 0.796 | 0.075 |
| Finland | 0.940 | 0.921 | 0.019 | 0.905 | 0.937 | 0.781 | 0.768 | 0.013 | 0.760 | 0.775 | 0.167 |
| France | 0.913 | 0.892 | 0.021 | 0.873 | 0.909 | 0.740 | 0.724 | 0.016 | 0.716 | 0.732 | 0.189 |
| United Kingdom | 0.918 | 0.895 | 0.023 | 0.878 | 0.913 | 0.773 | 0.751 | 0.023 | 0.739 | 0.762 | 0.161 |
| Greece | 0.885 | 0.852 | 0.032 | 0.829 | 0.877 | 0.705 | 0.687 | 0.018 | 0.678 | 0.697 | 0.194 |
| Hungary | 0.891 | 0.861 | 0.030 | 0.839 | 0.885 | 0.724 | 0.704 | 0.020 | 0.694 | 0.714 | 0.184 |
| Ireland | 0.942 | 0.922 | 0.020 | 0.904 | 0.938 | 0.789 | 0.774 | 0.014 | 0.766 | 0.782 | 0.160 |
| Iceland | 0.941 | 0.915 | 0.026 | 0.890 | 0.938 | 0.710 | 0.695 | 0.015 | 0.687 | 0.702 | 0.241 |
| Israel | 0.884 | 0.855 | 0.028 | 0.832 | 0.878 | 0.706 | 0.687 | 0.018 | 0.678 | 0.697 | 0.201 |
| Italy | 0.857 | 0.831 | 0.026 | 0.815 | 0.848 | 0.734 | 0.717 | 0.017 | 0.707 | 0.726 | 0.139 |
| Japan | 0.911 | 0.884 | 0.027 | 0.863 | 0.906 | 0.804 | 0.773 | 0.030 | 0.760 | 0.788 | 0.125 |
| South Korea | 0.905 | 0.877 | 0.028 | 0.854 | 0.899 | 0.797 | 0.774 | 0.023 | 0.763 | 0.785 | 0.118 |
| Lithuania | 0.798 | 0.756 | 0.042 | 0.731 | 0.786 | 0.702 | 0.687 | 0.015 | 0.679 | 0.695 | 0.092 |
| Luxembourg | 0.980 | 0.965 | 0.015 | 0.936 | 0.979 | 0.716 | 0.701 | 0.015 | 0.694 | 0.709 | 0.273 |
| Latvia | 0.892 | 0.865 | 0.027 | 0.845 | 0.885 | 0.731 | 0.715 | 0.016 | 0.706 | 0.723 | 0.173 |
| Mexico | 0.882 | 0.852 | 0.030 | 0.829 | 0.875 | 0.809 | 0.749 | 0.060 | 0.726 | 0.777 | 0.121 |
| Netherlands | 0.908 | 0.877 | 0.031 | 0.849 | 0.903 | 0.767 | 0.733 | 0.034 | 0.718 | 0.749 | 0.166 |
| New Zealand | 0.939 | 0.917 | 0.022 | 0.897 | 0.936 | 0.772 | 0.755 | 0.017 | 0.746 | 0.764 | 0.177 |
| Poland | 0.813 | 0.772 | 0.041 | 0.747 | 0.800 | 0.789 | 0.775 | 0.014 | 0.768 | 0.782 | 0.011 |
| Portugal | 0.907 | 0.882 | 0.025 | 0.861 | 0.902 | 0.766 | 0.745 | 0.020 | 0.735 | 0.756 | 0.155 |
| Slovakia | 0.845 | 0.810 | 0.035 | 0.790 | 0.834 | 0.714 | 0.686 | 0.029 | 0.673 | 0.700 | 0.155 |
| Slovenia | 0.883 | 0.856 | 0.027 | 0.837 | 0.877 | 0.726 | 0.710 | 0.016 | 0.702 | 0.718 | 0.171 |
| Sweden | 0.889 | 0.853 | 0.035 | 0.827 | 0.882 | 0.765 | 0.749 | 0.016 | 0.741 | 0.757 | 0.123 |
| Turkey | 0.862 | 0.839 | 0.033 | 0.804 | 0.855 | 0.787 | 0.741 | 0.028 | 0.746 | 0.773 | 0.116 |
| United States | 0.918 | 0.889 | 0.028 | 0.866 | 0.912 | 0.783 | 0.761 | 0.022 | 0.750 | 0.772 | 0.145 |
| Total | 0.894 | 0.866 | 0.028 | 0.845 | 0.888 | 0.757 | 0.735 | 0.022 | 0.725 | 0.746 | 0.152 |
| St.dev | 0.037 | 0.043 | 0.006 | 0.043 | 0.040 | 0.032 | 0.029 | 0.010 | 0.029 | 0.030 | 0.048 |
| Min | 0.798 | 0.756 | 0.015 | 0.731 | 0.786 | 0.702 | 0.686 | 0.013 | 0.673 | 0.695 | 0.022 |
| Max | 0.980 | 0.965 | 0.042 | 0.936 | 0.979 | 0.809 | 0.787 | 0.060 | 0.778 | 0.796 | 0.263 |

Notes: VRS technical efficiency bias-corrected scores estimated using 2000 bootstrap repetitions.

# Table 5: The characteristics of most and least efficient schools: descriptive statistics, by country.

Panel A: Schools in the 10% of most efficient schools, internationally

| Country | n efficient | STRATIO | EDUSHORT | ESCS | PVMATH1 | PVREAD1 | PVSCIE1 | n total (country) | % efficient (country) | % efficient (frontier) |
|---|---|---|---|---|---|---|---|---|---|---|
| | (a) | (b) | (c) | (d) | (e) | (f) | (g) | (h) | (i)=a/h | (j)=a/882 |
| Australia | 34 | 16.537 | 0.674 | 4.823 | 579.36 | 596.01 | 587.60 | 609 | 5.58% | 3.85% |
| Belgium | 33 | 12.243 | 1.327 | 4.719 | 599.58 | 588.35 | 590.37 | 236 | 13.98% | 3.74% |
| Switzerland | 33 | 15.982 | 1.091 | 4.642 | 608.75 | 583.88 | 589.28 | 217 | 15.21% | 3.74% |
| Chile | 14 | 26.564 | 0.852 | 3.800 | 472.03 | 524.10 | 501.00 | 202 | 6.93% | 1.59% |
| Colombia | 13 | 34.460 | 2.284 | 2.785 | 426.77 | 459.57 | 455.99 | 240 | 5.42% | 1.47% |
| Czech Republic | 80 | 12.402 | 1.601 | 4.526 | 592.34 | 592.16 | 595.80 | 321 | 24.92% | 9.07% |
| Germany | 48 | 13.366 | 1.759 | 4.543 | 574.12 | 588.23 | 586.07 | 177 | 27.12% | 5.44% |
| Denmark | 6 | 28.343 | 1.006 | 4.786 | 597.02 | 600.15 | 570.99 | 254 | 2.36% | 0.68% |
| Spain | 20 | 18.490 | 2.144 | 4.142 | 527.72 | 539.73 | 535.97 | 969 | 2.06% | 2.27% |
| Estonia | 56 | 11.128 | 1.700 | 4.175 | 562.11 | 578.40 | 577.78 | 229 | 24.45% | 6.35% |
| Finland | 18 | 12.108 | 1.840 | 4.719 | 552.82 | 580.27 | 570.15 | 194 | 9.28% | 2.04% |
| France | 21 | 11.863 | 1.253 | 4.571 | 572.61 | 581.02 | 575.32 | 197 | 10.66% | 2.38% |
| United Kingdom | 29 | 15.382 | 1.755 | 4.715 | 564.93 | 578.43 | 568.04 | 328 | 8.84% | 3.29% |
| Greece | 4 | 9.859 | 1.384 | 4.104 | 521.29 | 586.12 | 556.01 | 227 | 1.76% | 0.45% |
| Hungary | 19 | 11.304 | 2.309 | 4.681 | 583.86 | 583.79 | 582.99 | 215 | 8.84% | 2.15% |
| Iceland | 0 | - | - | - | - | - | - | 146 | 0.00% | 0.00% |
| Ireland | 15 | 13.975 | 2.263 | 4.478 | 531.89 | 567.05 | 536.60 | 125 | 12.00% | 1.70% |
| Israel | 16 | 16.142 | 2.437 | 4.824 | 535.09 | 566.97 | 548.78 | 154 | 10.39% | 1.81% |
| Italy | 33 | 11.547 | 1.759 | 4.278 | 583.45 | 572.01 | 560.35 | 474 | 6.96% | 3.74% |
| Japan | 45 | 13.208 | 2.178 | 4.315 | 598.74 | 584.06 | 605.39 | 183 | 24.59% | 5.10% |
| South Korea | 41 | 12.901 | 1.890 | 4.402 | 586.60 | 575.44 | 579.76 | 187 | 21.93% | 4.65% |
| Lithuania | 13 | 10.766 | 1.555 | 4.551 | 589.82 | 589.44 | 586.48 | 361 | 3.60% | 1.47% |
| Luxembourg | 0 | - | - | - | - | - | - | 38 | 0.00% | 0.00% |
| Latvia | 9 | 17.976 | 1.262 | 3.911 | 549.45 | 536.77 | 548.25 | 290 | 3.10% | 1.02% |
| Mexico | 47 | 45.074 | 2.116 | 2.922 | 444.96 | 463.85 | 457.15 | 280 | 16.79% | 5.33% |
| Netherlands | 34 | 21.949 | 0.978 | 4.768 | 602.33 | 576.28 | 594.58 | 136 | 25.00% | 3.85% |
| New Zealand | 15 | 14.513 | 1.215 | 4.602 | 546.44 | 581.08 | 575.52 | 179 | 8.38% | 1.70% |
| Poland | 43 | 8.118 | 1.561 | 4.328 | 581.87 | 588.81 | 579.47 | 240 | 17.92% | 4.88% |
| Portugal | 18 | 11.976 | 1.892 | 3.882 | 547.29 | 549.18 | 543.89 | 242 | 7.44% | 2.04% |
| Slovakia | 20 | 16.363 | 2.191 | 4.385 | 575.11 | 560.62 | 560.00 | 349 | 5.73% | 2.27% |
| Slovenia | 23 | 8.173 | 1.056 | 4.527 | 580.09 | 581.33 | 584.04 | 314 | 7.32% | 2.61% |
| Sweden | 15 | 13.558 | 0.748 | 4.763 | 577.55 | 614.66 | 590.40 | 194 | 7.73% | 1.70% |
| Turkey | 49 | 15.389 | 0.769 | 3.162 | 520.40 | 534.37 | 533.50 | 184 | 26.63% | 5.56% |
| United States | 18 | 23.628 | 1.232 | 4.620 | 532.01 | 566.96 | 559.82 | 134 | 13.43% | 2.04% |
| Total | 882 | 15.983 | 1.576 | 4.298 | 562.66 | 568.98 | 566.79 | 8825 | 9.99% | 100.00% |

Panel B: Schools in the 10% of most inefficient schools, internationally

| Country | n efficient | STRATIO | EDUSHORT | ESCS | PVMATH1 | PVREAD1 | PVSCIE1 | n total (country) | % inefficient (country) | % inefficient (frontier) |
|---|---|---|---|---|---|---|---|---|---|---|
| | (a) | (b) | (c) | (d) | (e) | (f) | (g) | (h) | (i)=a/h | (j)=a/882 |
| Australia | 21 | 10.960 | 1.347 | 4.087 | 387.08 | 375.42 | 386.62 | 609 | 3.45% | 2.38% |
| Belgium | 24 | 5.682 | 1.617 | 3.485 | 382.53 | 360.94 | 368.10 | 236 | 10.17% | 2.72% |
| Switzerland | 15 | 9.533 | 0.896 | 3.868 | 424.73 | 381.44 | 402.95 | 217 | 6.91% | 1.70% |
| Chile | 26 | 12.519 | 1.510 | 2.806 | 324.03 | 341.05 | 344.75 | 202 | 12.87% | 2.95% |
| Colombia | 22 | 19.013 | 2.198 | 2.864 | 337.40 | 344.05 | 356.40 | 240 | 9.17% | 2.49% |
| Czech Republic | 27 | 11.540 | 1.481 | 3.347 | 396.43 | 372.86 | 380.09 | 321 | 8.41% | 3.06% |
| Germany | 20 | 9.940 | 1.861 | 3.199 | 375.18 | 360.41 | 368.38 | 177 | 11.30% | 2.27% |
| Denmark | 15 | 10.867 | 1.072 | 3.931 | 414.58 | 391.02 | 391.20 | 254 | 5.91% | 1.70% |
| Spain | 31 | 9.413 | 1.735 | 3.461 | 403.63 | 367.80 | 389.94 | 969 | 3.20% | 3.51% |
| Estonia | 2 | 9.888 | 1.349 | 3.763 | 420.97 | 404.27 | 405.44 | 229 | 0.87% | 0.23% |
| Finland | 7 | 9.421 | 1.467 | 3.615 | 362.23 | 343.42 | 375.95 | 194 | 3.61% | 0.79% |
| France | 38 | 11.008 | 1.481 | 3.419 | 380.83 | 370.66 | 380.41 | 197 | 19.29% | 4.31% |
| United Kingdom | 5 | 15.863 | 1.795 | 4.022 | 416.70 | 396.57 | 407.58 | 328 | 1.52% | 0.57% |
| Greece | 56 | 8.362 | 1.951 | 3.321 | 360.47 | 345.75 | 361.67 | 227 | 24.67% | 6.35% |
| Hungary | 55 | 9.135 | 1.789 | 3.149 | 380.52 | 361.94 | 372.02 | 215 | 25.58% | 6.24% |
| Iceland | 7 | 8.735 | 1.388 | 4.147 | 420.66 | 396.02 | 413.34 | 146 | 4.79% | 0.79% |
| Ireland | 0 | - | - | - | - | - | - | 125 | 0.00% | 0.00% |
| Israel | 51 | 9.294 | 1.923 | 3.914 | 364.11 | 348.71 | 359.90 | 154 | 33.12% | 5.78% |
| Italy | 81 | 7.075 | 1.926 | 3.398 | 378.28 | 355.83 | 364.51 | 474 | 17.09% | 9.18% |
| Japan | 3 | 8.115 | 2.228 | 3.943 | 437.47 | 400.15 | 427.80 | 183 | 1.64% | 0.34% |
| South Korea | 8 | 9.971 | 1.648 | 3.654 | 400.87 | 384.20 | 393.78 | 187 | 4.28% | 0.91% |
| Lithuania | 92 | 8.237 | 1.355 | 3.646 | 391.13 | 362.80 | 382.29 | 361 | 25.48% | 10.43% |
| Luxembourg | 2 | 7.677 | 1.187 | 3.399 | 409.94 | 376.74 | 394.70 | 38 | 5.26% | 0.23% |
| Latvia | 21 | 9.206 | 1.384 | 3.699 | 415.34 | 374.92 | 395.48 | 290 | 7.24% | 2.38% |
| Mexico | 19 | 14.976 | 2.062 | 2.657 | 336.64 | 344.74 | 347.82 | 280 | 6.79% | 2.15% |
| Netherlands | 26 | 14.250 | 1.068 | 3.929 | 421.63 | 381.66 | 398.10 | 136 | 19.12% | 2.95% |
| New Zealand | 5 | 13.430 | 1.632 | 3.486 | 387.20 | 384.86 | 380.27 | 179 | 2.79% | 0.57% |
| Poland | 5 | 9.427 | 0.397 | 3.486 | 386.83 | 376.26 | 375.98 | 240 | 2.08% | 0.57% |
| Portugal | 19 | 9.114 | 2.317 | 2.981 | 359.81 | 346.25 | 370.06 | 242 | 7.85% | 2.15% |
| Slovakia | 92 | 11.503 | 1.778 | 3.269 | 396.77 | 358.44 | 374.49 | 349 | 26.36% | 10.43% |
| Slovenia | 59 | 6.496 | 1.384 | 3.571 | 391.05 | 367.17 | 379.27 | 314 | 18.79% | 6.69% |
| Sweden | 10 | 8.587 | 0.995 | 4.008 | 407.18 | 388.49 | 387.25 | 194 | 5.15% | 1.13% |
| Turkey | 15 | 10.645 | 1.351 | 2.510 | 366.89 | 356.10 | 370.89 | 184 | 8.15% | 1.70% |
| United States | 3 | 9.888 | 1.963 | 3.994 | 328.81 | 319.01 | 355.88 | 134 | 2.24% | 0.34% |
| Total | 882 | 9.763 | 1.636 | 3.442 | 383.12 | 361.83 | 374.85 | 8825 | 9.99% | 100.00% |

Notes: The most efficient schools are those which efficiency score is above the 90th percentile, while the least efficient ones have an efficiency score below the 10th percentile. Efficiency measured under the international frontier.

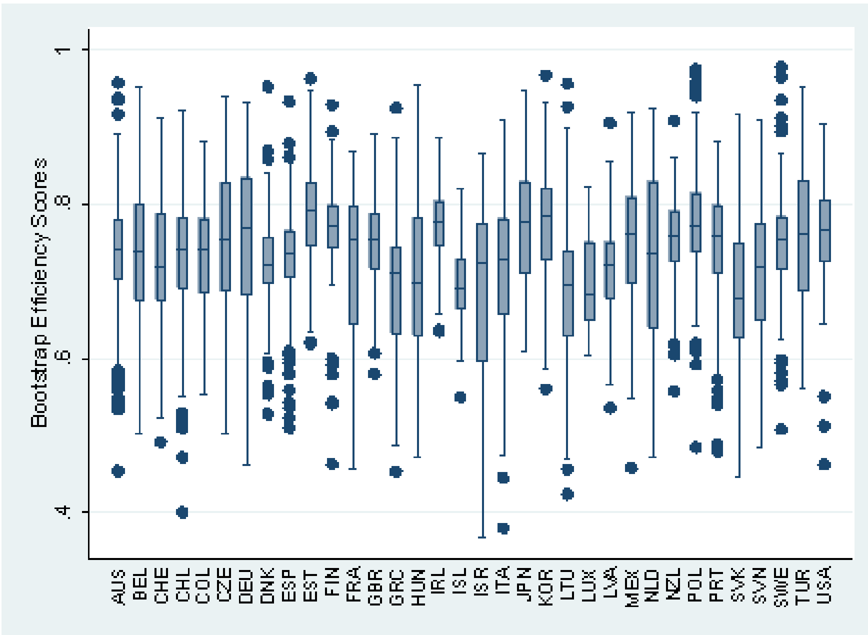
## Table 6: Factors associated with technology gaps

| | Model 1 | | | Model 2 | | | Model 3 | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Variables | Coef. (SE) | CILB | CIUP | Coef. (SE) | CILB | CIUP | Coef. (SE) | CILB | CIUP | |
| | | | | Students' Features | | | | | | |
| AGE | -0.058*** | -0.047 | -0.036 | -0.044*** | -0.086 | -0.012 | -0.041*** | -0.027 | -0.054 | (-10.07) |
| | (-7.24) | | | (-6.17) | | | | | | |
| SEX | -0.041*** | -0.033 | -0.016 | -0.032*** | -0.069 | -0.014 | -0.028 | -0.021 | -0.036 | (11.71) |
| | (-8.37) | | | (7.24) | | | | | | |
| REPEAT | 0.078*** | 0.054 | 0.082 | 0.084*** | 0.059 | 0.101 | 0.081*** | 0.074 | 0.089 | (23.81) |
| | (24.45) | | | (21.72) | | | | | | |
| HOMEWORK | -0.021*** | -0.025 | -0.017 | -0.001*** | -0.002 | 0.000*** | -0.062 | -0.241 | 0.123 | (5.17) |
| | (6.44) | | | (5.84) | | | | | | |
| IMMIG | 0.001 | -0.001 | 0.018 | 0.000 | -0.010 | 0.020 | 0.000 | 0.000 | 0.000 | (1.46) |
| | (1.15) | | | (0.98) | | | | | | |
| ESCSSD | 0.018*** | 0.012 | 0.036 | 0.016*** | 0.008 | 0.025 | 0.021*** | 0.014 | 0.029 | (5.59) |
| | (4.68) | | | (5.61) | | | | | | |
| STACCURACY | 0.008*** | 0.000 | 0.018 | 0.002*** | 0.000 | 0.004 | 0.008*** | 0.002 | 0.015 | (6.17) |
| | (5.08) | | | (5.04) | | | | | | |
| | | | | School's Features | | | | | | |
| RURAL | | | | 0.009*** | 0.001 | 0.019 | 0.007*** | 0.003 | 0.012 | |
| | (7.24) | | | (5.29) | | | | | | |
| PRIV | | | | -0.005*** | -0.008 | -0.003 | -0.002*** | -0.004 | -0.000 | |
| | (2.44) | | | (10.90) | | | | | | |
| ORIENT | | | | 0.021*** | 0.011 | 0.030 | 0.022*** | 0.018 | 0.027 | |
| | (4.19) | | | (5.12) | | | | | | |
| CLASSSIZE | | | | -0.007*** | -0.012 | -0.003 | -0.006*** | -0.008 | -0.004 | |
| | (4.01) | | | (3.32) | | | | | | |
| SCHSIZE | | | | -0.000*** | -0.002 | -0.000 | -0.000*** | -0.000 | -0.000 | |
| | (10.29) | | | (6.05) | | | | | | |
| SCHSIZE2 | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | |
| | (1.24) | | | (1.15) | | | | | | |
| | | | | School's Practices and Processes | | | | | | |
| FUND1 | | | | | | | -0.001 | 0.001 | 0.0059 | |
| | | | | (1.24) | | | | | | |
| FUND2 | | | | | | | -0.001*** | -0.0031 | 0.0022 | |
| | | | | (1.24) | | | | | | |
| CERT | | | | | | | -0.003*** | -0.0163 | -0.0044 | |
| | | | | (2.71) | | | | | | |
| ACCOUNT | | | | | | | 0.001*** | 0.0022 | 0.0032 | |
| | | | | (5.24) | | | | | | |
| EXTEVAL | | | | | | | 0.001*** | 0.0028 | 0.0048 | |
| | | | | (3.87) | | | | | | |
| POORREL | | | | | | | -0.009*** | -0.001 | -0.001 | |
| | | | | (2.32) | | | | | | |
| COMPET | | | | | | | 0.001*** | 0.0013 | 0.0036 | |
| | | | | (5.01) | | | | | | |
| PERCOMP | | | | | | | -0.001*** | 0.0013 | 0.0036 | |
| | | | | (3.54) | | | | | | |
| DISCCLIMATE | | | | | | | -0.000 | -0.006 | -0.001 | |
| | | | | (1.07) | | | | | | |
| EXTRACURRA | | | | | | | -0.002*** | -0.006 | 0.000 | |
| | | | | (4.24) | | | | | | |
| Constant | -0.063 | -0.241 | 0.123 | 0.151* | -0.082 | 0.356 | 2.412*** | 0.711 | 4.113 | (-0.71) |
| | (1.54) | | | (2.78) | | | | | | |
| Country dummies | | Yes | | | Yes | | | Yes | | |
| Wald-$X^2$ | | 1069.08 | | | 1294.28 | | | 2064.74 | | |
| Number of observations | | 7339 | | | 7339 | | | 7339 | | |

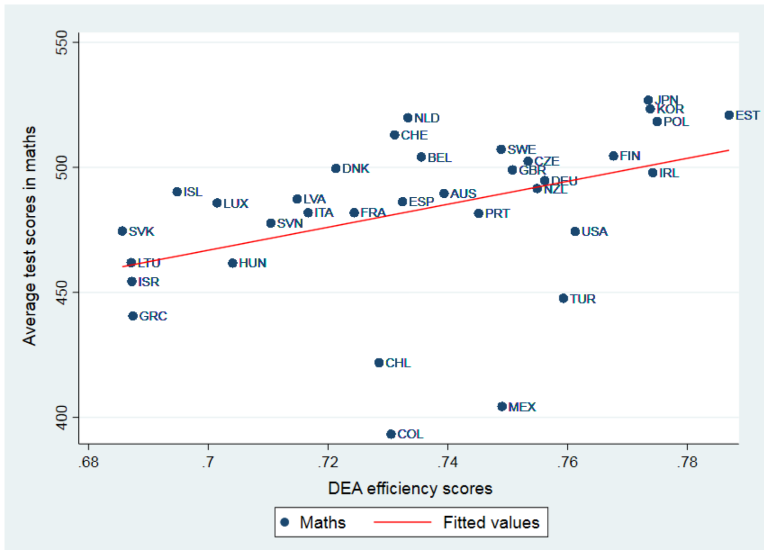
Notes: Significance level: *** p<0.01, ** p<0.05, * p<0.1

## B Appendix

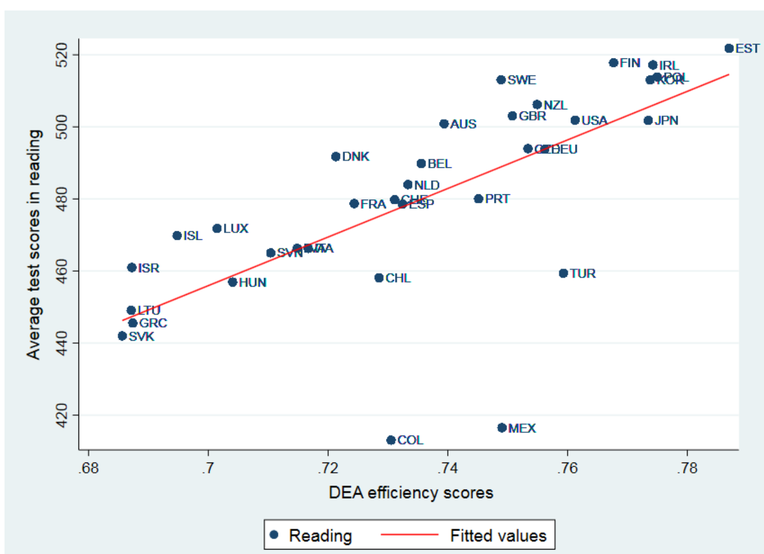
Figure 1: The distribution of efficiency scores under country frontier technology




Note:.



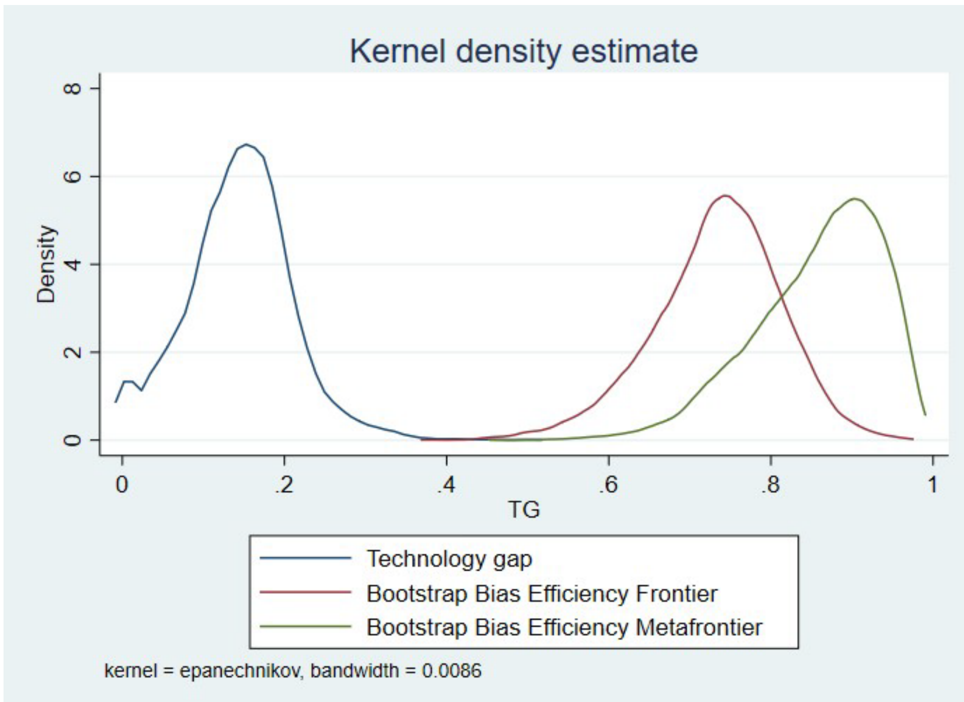

(a) Efficiency scores and maths performance of the national frontier




(b) Efficiency scores and reading performance of the national frontier

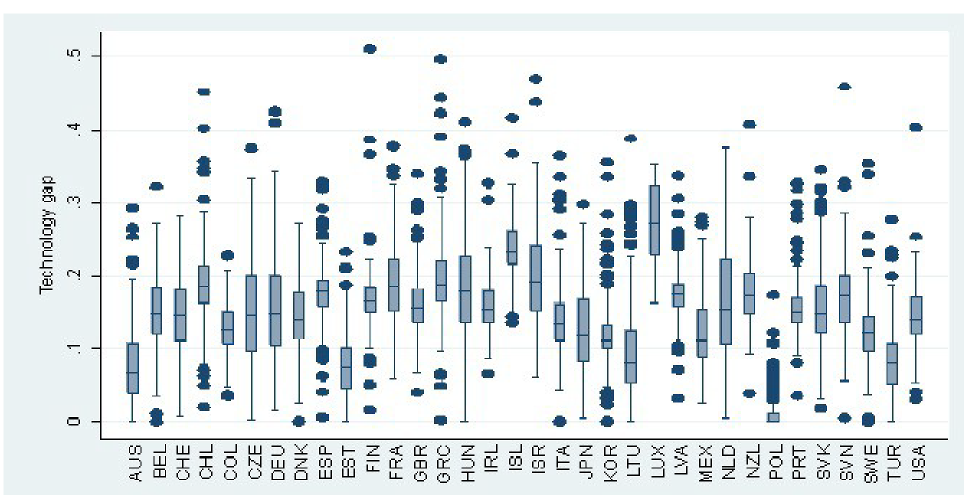
Figure 2: Relationship between efficiency scores, maths and reading performance.

Figure 3: Kernel densities for efficiency, meta-efficiency scores and technological gaps




Note:

Figure 4: The distribution of technology gap




Note: