The effect of ICT on schools' efficiency: Empirical evidence on 23 European Countries

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Abstract

In the last two decades, ICT use in schools grew exponentially. In this paper, the relationship between ICT and school's efficiency and the mechanisms through which ICT can enhance schools' productivity are investigated, using PISA 2018 data for about 5400 schools. Empirically, we analyze school's efficiency in producing ICT-mediated instructional time as well as final educational output, by implementing a network Data Envelopment Analysis (DEA) model. The analysis is complemented by a conditional DEA to account for the presence of possible external drivers of schools' efficiency. Results show that the average schools' efficiency in using ICT is relatively low, and that it is mainly driven by the ability of translating ICT-mediated instructional time into learning, rather than by the amount of ICT and human resources. This evidence is consistent across countries. By investigating the role of ICT in schools' efficiency the paper provides insights to guide the transition of digital technology into learning.

Keywords: Schools' efficiency, ICT, Data envelopment analysis.
JEL codes: I20, I21, I29.

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1 Introduction

The last two academic years (2019/20 and 2020/21) have been dramatically disrupted by the emergency induced by COVID-19, which implied long periods of school closure and a massive use of digital technologies for guaranteeing educational continuity (Daniel, 2020; Schleicher, 2020). The adoption of digital tools during the COVID-19 period (and beyond) represents a major change for the educational systems across the globe and imposes a reflection about the effectiveness of their use for teaching purposes. Several research has been devoted to exploring the effects of COVID-related school closures on students' learning (see a review in Gambi and De Witte, 2021), but few studies explicitly try to disentangle the mechanisms and reasons behind such a learning loss (see for example Tomasik et al., 2021). Previous empirical evidence demonstrates a decline in academic results during the academic years affected by the COVID disruption (Patrinos & Donnelly, 2021). It is challenging to address whether this learning loss can be attributed to the use of digital technologies in the educational process or to side effects of the pandemic situation, such as school closure, solitary confinement and a general situation of stress (Onyema et al., 2020). As a matter of fact, it is likely that more technologically equipped schools, as well as those more technologically savvy in the use of distance learning, could be able to generate better academic outcomes for their students when compared with less prepared or equipped counterparts, all else equal. In different terms, the impact of technology on students' results could be different depending upon the specific characteristics of the school in leveraging on technology for learning. Understanding the conditions under which technology can support learning effectiveness is the main motivation for this study.

A complementary perspective on the same topic relates with the efficiency in the use of information and communication technologies (ICT) within schools. Efficiency in the use of ICT can be defined as the ability of maximizing students' learning with the available resources, including the technological ones and their interaction with other factors, like teachers and facilities, and this is a managerial task. Measuring efficiency is challenging, though, because the schools' production process involves a complex transformation of multiple inputs (students' ability, resources, etc.) into many outputs (e.g. learning in different subjects). On one side, different results across schools could be due to different availability of ICT (more/less laptops, better/worse broadband, etc.). On the other side, schools might be heterogeneously able to use the available ICT resources for educational activities – so, to translate their use in effective teaching and subsequent learning results – for any given level of resources available, suggesting a possible decomposition of the schools' production function. Previous studies demonstrate that schools have different efficiency levels between and within countries (Agasisti & Zoido, 2018), but research about how ICT use and availability is correlated with schools' efficiency is still missing.

The performance and efficiency of schools is also affected by contextual factors that are not under their managerial control, as discussed by Afonso and Aubyn (2006), Agasisti and Zoido (2019), and Aparicio et al. (2018), among others. Analyses about the performance of educational institutions must consider this aspect as a very important one, to avoid deriving policy implications affected by heterogeneity that cannot be managed by school principals and teachers (Mergoni & De Witte, 2021a). This caution is particularly decisive in the context of cross-country comparisons, where differences in the efficiency of schools can be particularly influenced by structural characteristics of the educational systems (as for example, selectivity, autonomy over budget, teachers' training policies, etc.). [1]

This paper aims at exploring the efficiency of schools in 23 countries located in Europe, using data from the 2018 edition of OECD's Programme for International Student Assessment (PISA). In so doing, the production process is modelled considering teachers and ICT resources as inputs, and (standardized) test scores in mathematics, reading and science as outputs. A school is deemed as efficient if it maximizes the outputs (students' test scores in the selected disciplines) given the observed level of resources available. Data Envelopment Analysis (DEA), a non-parametric approach, is employed for the empirical assessment of efficiency, as specified in section 2. The overall efficiency score for each school is decomposed in two sources: the efficiency in securing ICT resources, considered as a key input in producing learning (first stage), and the efficiency in using ICT for education (second stage) – methodologically-wise, a network DEA is used for this purpose (Färe et al., 2007; Kao & Hwang, 2008). Also, the paper takes into account some environmental factors that can affect the efficiency of the learning process. In detail, the following research questions are investigated: (i) what is the efficiency of schools in providing ICT instructional time given the ICT resources and in transforming these inputs into academic achievement? (ii) which of the two components (ICT resources or its usage) is more important in affecting the overall efficiency of the schools? (iii) which is the effect of the selected contextual variables (shortage of educational resources, school track and students' socioeconomic status - SES) on schools' efficiency?

[1] The academic literature suggests various methodological approaches to deal with schools' efficiency estimation in presence of structural, country-level differences. This paper adopts a method based on the concept of local and conditional efficiency, following Rao et al. (2003) and Cordero et al. (2017), as detailed in section 2.

The present research is innovative in multiple ways. First, this is the first contribution that measures the efficiency of the schools explicitly modelling the available and used ICT resources as inputs – something that is crucially important in the post-COVID situation for most educational systems. Second, the use of network DEA allows understanding the mechanisms that drive the efficient use of ICT in schools, separating the available resources from its effective use in teaching – and this investigation is conducted with a proper methodological approach for the first time. Third, this paper provides the first systematic literature review over the applications of network-DEA models to education. Fourth, this is one of the few papers that explore the impact of key contextual variables (specifically, the school track, the socioeconomic condition of the students and the quality of educational resources) on schools' efficiency with a robust methodology, namely conditional DEA (few exceptions already exist, like Cordero et al., 2018; Haelermans and De Witte, 2012).

To anticipate the main findings of this paper, three notable indications emerge. First, the average level of efficiency is low in all countries, about 0.58 (out of 1), indicating that most schools are characterized by a high level of inefficiency. Second, the efficient use of ICT resources for educational purposes is more important in determining the overall schools' efficiency than the mere ICT availability, especially in lower tracks. Third, the efficiency of the schools is positively correlated with low shortage of educational resources and with a more advantaged socioeconomic status of the students.

The remainder of the paper is organized as follows. Section 2 illustrates the methodological strategy employed in this paper, while section 3 describes the dataset used for the empirical analyses. Section 4 contains the results and a critical discussion about them. Section 5 concludes, also deriving policy implications from the findings.

2 Methodology

2.1 Measuring schools' efficiency: Data Envelopment Analysis

Non-parametric frontier approaches are well accepted methods to measure efficiency in contexts where the production function is unknown or not easily retrieved, as it is the case of schools and other education institutions. According to this approach, the efficiency of a school (and more in general of any Decision Making Unit - DMU) is defined as the ability of transforming a number of inputs in a number of outputs, relative to the ability of the other schools in the sample. This definition comes from Farrell (1957) and has been operationalized via a linear programming estimator by Charnes et al. (1978).

In this framework, the efficient frontier is constructed empirically as the smaller frontier which envelops all the units in the input-output space and the efficiency scores are measured in terms of radial distance from the frontier. This approach is also known as Data Envelopment Analysis (DEA) and is well accepted for an ample spectrum of applications, including education (see for example the papers by Aparicio et al., 2018; De Witte and López-Torres, 2017; Silva et al., 2020). In particular, the main advantages are that it is flexible (as it relies on a smalls set of assumptions), objective (as it provides an aggregate measure using an endogenous and objectively defined weighting system), and easy to interpret (as it delivers a scalar measure of efficiency, bounded between 0 and 1, where 1 is assigned to the best DMU).

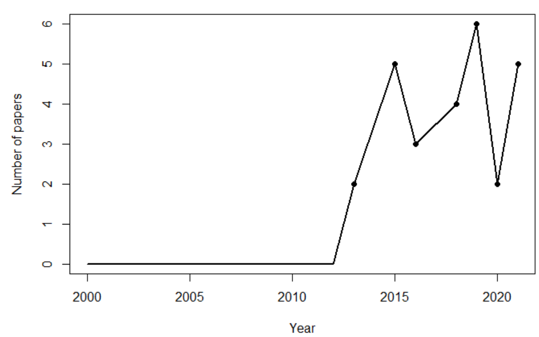
However, conventional DEA tends not to use the information about the internal structures of the production technology and therefore it considers the productive process of the DMU as a black-box (Cook, Zhu, et al., 2010). Consequently, the traditional DEA models offer only murky insights about how to improve the performance of the DMU (C.-M. Chen, 2009; Homburg, 2001). To overcome this issue, Charnes et al. (1986) introduced the idea of network model, then developed by Färe (1991) and Färe and Grosskopf (1996, 2000), who introduced a specific methodology to explicitly account for the presence of intermediate measures, i.e., inputs that are produced and consumed within the production process. Network models allow to shed some light on the operation of the production technology and to evaluate how the performance decomposes into the intermediate stages within the DMUs (details are offered in the paragraph 2.2). In particular, the two stage network models account for the trade-off that emerges, since the intermediate measures are maximized in the first stage (i.e., treated as outputs), but minimized in the second (i.e., treated as inputs), in order to increase efficiency (Cook, Liang, et al., 2010).

2.2 Opening the black-box: network DEA

As highlighted by Tone and Tsutsui (2009), network structures are particularly interesting when evaluating a business characterized by a complex structure and multiple stages, such as electric power companies, hospitals, broadcasting companies and financial holding companies. Nevertheless, the application of network models is significantly wider, as highlighted by Lee and Worthington (2016) and Lee and Johnes (2021), who report studies on airports, banks, hotels, electric utilities, university libraries and research and development.

To the best of our knowledge, the application of network model to education has been developed in the literature only to a marginal extent. By searching in Scopus, EBSCOhost (which contains ERIC), and Web of Science the string "network data envelopment analysis" and "education", 24 papers have been selected. Figure 1 shows that since 2013 there has been an important growth in the number of papers published on the topic, revealing the growing interest in the application of network DEA techniques for the evaluation of universities and schools' performance.

Figure 1: Papers Applying Network DEA in Education

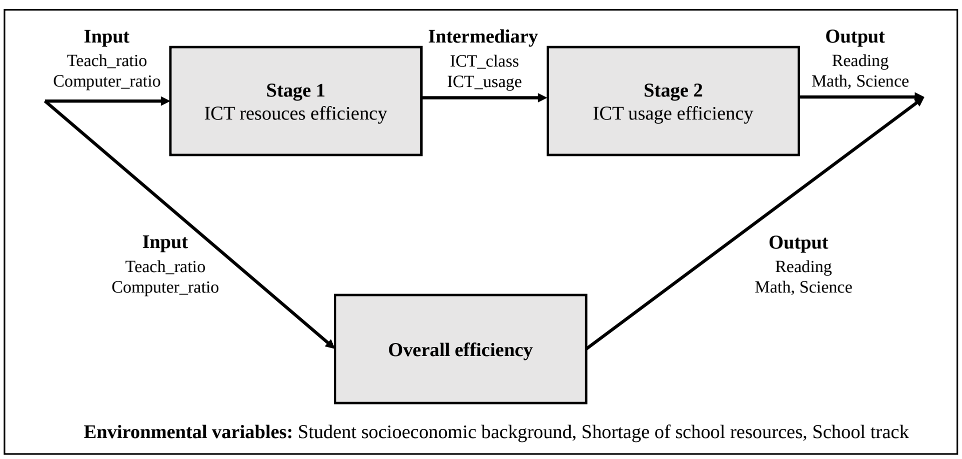


Source: authors elaboration considering publications in Scopus, EBSCOhost and Web of Science up to October 2021

As reported from table 1, the great majority of the studies are focused on higher education (23 papers, excluding a paper on post-secondary non-tertiary education in Australia (C.-T. Tran, 2021)). Only 3 papers implement a network DEA to evaluate the performance of primary and secondary schools and school districts. Interestingly, the schools considered in these studies are located in North America (Avilés Sacoto et al., 2015; Grosskopf et al., 2015) and Australia (Wanke et al., 2016). To the best of our knowledge no paper implemented a network DEA to evaluate the performance of secondary schools in Europe, therefore, this is an innovative and specific contribution of the present paper. As for the methodology, the papers are categorized according with the network structure used or according with the DEA method implemented to measure the efficiency (Kao, 2014). The most common network structures are the two stage ones, in particular, the teaching stage and the research stage (Y. Chen et al., 2021; Monfared & Safi, 2013), teaching stage and industry responsiveness (C.-T. Tran, 2021), financial division and academic division in (C.-D. Tran & Villano, 2018, 2021), and research stage and grant application stage (Lee & Worthington, 2016). Avilés Sacoto et al. (2015), Meza et al. (2018), and Tavares et al. (2021), instead, implement a three stage model. Regarding the DEA method implemented, the slack-based model by Tone and Tsutsui (2009, 2014) is common, in particular in the context of dynamic structures (Johnes, 2013; Lee & Johnes, 2021; Lobo et al., 2016; C.-D. Tran & Villano, 2018, 2021; C.-T. Tran, 2021). The slack-based is more flexible than the classical DEA model by Charnes et al. (1978) and Banker et al. (1984), as it does not rely on the assumption of proportional reduction of inputs (or increase of outputs, Tone, 2001).

In this study, the education production function is modeled as a basic two-stage process, as shown in figure 2, where the ICT usage for instructional time are adopted as intermediate measures.

Figure 2: The basic two-stage Network DEA model



In the first stage, schools are evaluated according with their ability of providing ICT usage for instructional time, given two inputs: the teacher-student ratio and the computer-student ratio, as proxies for human and technological resources, respectively. In the second stage, the use of ICT for instructional purposes is considered the input for maximizing student achievement, measured by PISA test scores in math, reading, and science. More details regarding these variables are given in the section 3. The efficiency measurement proposed for the evaluation of the overall efficiency is the non-cooperative and centralized model as in Liang et al. (2008) and Kao and Hwang (2008). In the centralized model, the two processes work jointly to achieve the final outcomes in an efficient way.

Formally, the overall efficiency of a school j_0 is defined as:

Table 1: Papers using network DEA in education. A synthetic categorization.

Panel 1: Papers by level of application

#	Level	Papers
23	higher education	public institutions (An et al., 2019; Y. Chen et al., 2021; Despotis et al., 2015; Ding et al., 2020; Tavares et al., 2021; C.-D. Tran & Villano, 2018, 2021; Visbal-Cadavid et al., 2019; Wang et al., 2019; Yang et al., 2018); private institutions (Johnes, 2013; Lee & Johnes, 2021; Shamohammadi & Oh, 2019); private and public or not specified (Aviles-Sacoto et al., 2015; Chodakowska, 2015; Lee & Worthington, 2016; Madria et al., 2019; Meza et al., 2018); departments (Kashim et al., 2018; Koronakos et al., 2019); colleges (Esmaeilzadeh & Matin, 2019; Monfared & Safi, 2013); university hospital (Lobo et al., 2016)
3	primary and/or secondary	Avilés Sacoto et al., 2015; Grosskopf et al., 2015; Wanke et al., 2016
1	post secondary	C.-T. Tran, 2021

Panel 2: Papers by geographical area of application

#	Continent	Papers
11	Asia	China (An et al., 2019; Y. Chen et al., 2021; Ding et al., 2020; Wang et al., 2019; Yang et al., 2018); Philippines (Madria et al., 2019); Korea (Shamohammadi & Oh, 2019); Vietnam (C.-D. Tran & Villano, 2018, 2021); Iran (Esmaeilzadeh & Matin, 2019; Monfared & Safi, 2013)
5	Europe	England (Johnes, 2013; Koronakos et al., 2019; Lee & Johnes, 2021); Poland (Chodakowska, 2015); Grece (Despotis et al., 2015)
4	South America	Brazil (Lobo et al., 2016; Meza et al., 2018; Tavares et al., 2021); Colombia (Visbal-Cadavid et al., 2019)
3	Australia	(Lee & Worthington, 2016; C.-T. Tran, 2021; Wanke et al., 2016)
3	North-Ameria	Mexico (Avilés Sacoto et al., 2015; Aviles-Sacoto et al., 2015); Texas (Grosskopf et al., 2015)

Panel 3: Papers by methodology implemented

#	Methodology	Papers
8	Basic two-stage	Aviles-Sacoto et al., 2015; Meza et al., 2018; Tavares et al., 2021 implemented a model similar to Kao and Hwang, 2008; Madria et al., 2019; Monfared and Safi, 2013 refer to the models in Cook, Liang, et al., 2010; Lee and Worthington, 2016; Shamohammadi and Oh, 2019; Wanke et al., 2016 implemented a model similar to Liang et al., 2008;
6	Dynamic structure	Johnes, 2013; Lee and Johnes, 2021 implement a model similar to Tone and Tsutsui, 2009; Lobo et al., 2016; C.-D. Tran and Villano, 2018, 2021; C.-T. Tran, 2021 implement a model similar to Tone and Tsutsui, 2014
4	General two-stage	Y. Chen et al., 2021 implemented a model similar to Y. Chen et al., 2010; An et al., 2019 similar to Liang et al., 2011; Yang et al., 2018 similar to Fukuyama and Weber, 2015; Chodakowska, 2015 use the model of Chiu et al., 2011
3	multi period two stage model	Koronakos et al., 2019; Wang et al., 2019 extend the model by Kao and Hwang, 2014; Esmaeilzadeh and Matin, 2019 extended the model of Kao and Hwang, 2008
1	hierarchical structure	Kashim et al., 2018
1	neural network	Visbal-Cadavid et al., 2019
4	other models	Grosskopf et al., 2015 implement a model with reallocation of resources; Avilés Sacoto et al., 2015 used the model of Cook et al., 2006; Ding et al., 2020 develop a model for the evaluation of general non-homogeneous DMUs based on the additive model of C.-M. Chen, 2009; Despotis et al., 2015 develop a model for two stage series processes

Note that one paper, Chodakowska (2015), use fictional data, so it is not possible to be included it in one of the geographical categories.

$$
\begin{aligned}
E^{overall} = max \qquad & \sum_{r=1}^{s} u_r y_{r0} \\
s.t. \qquad & \sum_{r=1}^{s} u_r y_{rj} \leq \sum_{d=1}^{k} w_d z_{dj} \qquad j = 1, ..., n \\
& \sum_{d=1}^{k} w_d z_{dj} \leq \sum_{i=1}^{m} v_i x_{ij} \qquad j = 1, ..., n \\
& \sum_{i=1}^{m} v_i x_{ij} = 1 \qquad w_d \geq 0; v_i \geq 0; u_r \geq 0
\end{aligned}
\tag{1}
$$

s is the number of outputs, m is the number of inputs, k is the number of intermediate goods; u_r is the weight relative to the the rth output, w_d is the weight relative to the the dth intermediate measure, and v_i is the weight relative to the i^{th} input. The rth outputs, dth intermediate measures and i^{th} input of school j are represented, respectively, by y_{rj}, z_{dj}, and x_{ij}. The overall efficiency can be decomposed as the product of the efficiencies of the two sub-processes: $E^{overall} = E^{stage1} \cdot E^{stage2}$. After the optimal weights u_r^*, w_d^*, and v_i^* are found from equation 1, the efficiencies of the single stages are obtained subsequently as:

$$E^{stage1} = \frac{\sum_{d=1}^{k} w_d^* z_{d0}}{\sum_{i=1}^{m} v_i^* x_{i0}} \tag{2}$$

$$E^{stage2} = \frac{\sum_{r=1}^{s} u_r^* y_{r0}}{\sum_{d=1}^{k} w_d^* z_{d0}} \tag{3}$$

In the context of non-parametric frontier estimation the efficiency scores are obtained in terms of distance from the best production frontier. In particular, the efficiency scores obtained from the linear optimization programming problems 1, 2, and 3 belong to the interval $(0, 1]$, where 1 is assigned to the efficient schools and a lower value indicate the proportional reduction of inputs that the schools could implement without decreasing the level of educational outcomes.

2.3 Considering heterogeneity: local frontiers and conditional analysis

The schools in our sample are located in different countries and this threats the homogeneity assumption, i.e., the assumption that the units considered in the sample are similar, or, at least they share the same production function. Indeed, the characteristics of the different educational systems are likely to affect the school's production process across countries. To overcome this issue country level frontiers are estimated by means of a metafrontier approach, therefore local efficiency scores are computed (Rao et al., 2003). The reasons that justify the construction of country level frontiers are similar to the reasons for which one might introduce country fixed effect in the context of a classical linear regression. The construction of country level frontiers allows to evaluate the schools only with respect to the other schools that operate in the same country (and not with all the other schools in the sample), therefore, it allows to account for the possible heterogeneity in cross-country education systems. At the same time, it is theoretically possible to measure the different efficiency levels of the different educational systems - something that this paper does not develop in details and is left for future research.

In addition to modeling cross-country heterogeneity, the analysis is complemented by a robust and conditional estimation, in line with the suggestion of Cazals et al. (2002) and Daraio and Simar (2005). This allows to account for the possible presence of outliers and for the influence of factors that are exogeneous, but relevant, for the transformation process (Cordero et al., 2017). Robust and conditional techniques have been developed for the classical DEA estimation. The logic behind these approaches is translated in the framework of a network DEA. The idea of robust and conditional DEA is that, to obtain unbiased scores, it is necessary to evaluate each unit not with respect to the full sample of n units, but with respect to a subset of m units ($m < n$). In particular, a bootstrap procedure is implemented to refine the sample of units to be included in the analysis. For each bootstrap replicate, m units are selected with replacement and an efficiency score is computed. The robust and conditional scores are then obtained as the average efficiency score obtained over the B bootstrap replicates. The difference between the robust and the conditional scores is inherent to the choice of the m units. In the case of the robust analysis, the units are chosen randomly and with replacement. In the case of the conditional analysis, the units are chosen accordingly with their similarity, so that each unit is evaluated with respect to units that are similar in terms of certain characteristics (i.e., exogenous variables). The implementation of the conditional analysis allows to compute *caeteris paribus* efficiency scores and therefore is fundamental to study the influence of the exogenous variables on efficiency. In the case proposed in this study, the aim is to consider the effect of certain factors out of the school control on their efficiency, in particular, the students' socioeconomic background, the quality of school resources, and the track (general or vocational). The choice of these variables is justified by three main elements: (i) the indications coming from the literature in the field, (ii) the policy relevance of these factors, and (iii) data availability - see section 3.

3 Data

Data are drawn from the Program for International Student Assessment (PISA) 2018 survey.[2] The survey measures the competences of 15 years-old pupils in mathematics, reading and science in 79 countries (the 37 OECD countries and 42 partner countries) and provides rich information regarding the educational environment, such as the student's socioeconomic background, the teacher attitude and the school context. In this paper, the focus is on the ICT familiarity questionnaire, which collects information regarding the ICT use and practice of students at schools and at home. This questionnaire was delivered to 52 countries. Among these, those located in the European geographical area were selected, yielding to a final sample of 23 countries. The analysis is implemented at the school level, thus, all the information available at student level has been aggregated by considering the school average, leading to a final sample of 5,406 schools.

The focus on the European context taken in the analysis is justified by three main factors. First, it is necessary to involve countries with similar ICT infrastructure. One of the assumption of the DEA is that all the DMUs (in our case the schools) in the sample have access to inputs with similar prices, so the price of human and technological capital should be similar in the countries under analysis. Second, an important assumption of DEA is homogeneity, which requires that the education production process of the DMUs in the analysis is similar. The more restrictively this assumption is interpreted, the lower the external validity of the analysis. Restricting the sample to European countries balances at best these two opposite interests. Third, it is necessary to involve countries with similar educational systems and political structure to provide meaningful policy recommendations; if there is no common background, it is neither possible to fine tune the recommendations reflecting the heterogeneity of the countries.

The variables involved in the analysis are reported in table 2. As inputs, the teacher-student ratio and the computer-teacher ratio are considered. These indicators are obtained from PISA using the variables SC002Q01TA and SC002Q02TA, which indicate the number of male and female students, SC018Q01TA01 and SC018Q01TA02, which indicate the number of full and part-time teachers, and the variable SC004Q02TA, which indicates the number of computers available for the students. The teacher-student ratio is commonly used in the literature as

[2]For additional information regarding the data, see the official website https://www.oecd.org/pisa/

a measure of the quantity of human resources available (Afonso & Aubyn, 2006; Agasisti & Zoido, 2018; Sutherland et al., 2010). In a similar strand, the computer-student ratio is used as a measure of the amount of resources available, with a specific focus on the technological resources (Mancebón et al., 2012). In our sample, Turkey is the country with the lowest level of inputs (1.08 for the teacher ratio and 1.06 for the computer ratio), while Poland reports the highest values (1.16 and 1.15, respectively). Despite no clear geographical pattern can be highlighted, a slight tendency can be detected, as Eastern Europe countries tend to have lower teacher and computer ratios.

The students' performance in the PISA test in mathematics (PV1 MATH), reading (PV1 READ) and science (PV1 SCIE) are considered as final outputs of the efficiency model. In this respect, student achievement is considered as the final result of the educational process, in line with previous studies (Afonso & Aubyn, 2006; De Witte & López-Torres, 2017). One of the main advantage of DEA is that it allows us to implement multidimensional evaluations, involving multiple inputs and outputs. From table 2 it can be noticed that countries that perform high scores (or low scores) in one of the PISA subjects, tend to perform similarly in the others. In particular, Bulgaria is the country with the lowest scores (429, 424 and 417 for math, reading and science, respectively), while Estonia (519, 520, 526) and Poland (520, 515 and 513) are those with the highest performance.

As intermediate measures (i.e. outputs for the first stage and inputs for the second), the frequency of ICT usage at school and the amount of instructional time mediated by ICT are considered. Such information was obtained through the variables USESCH and ICTCLASS, two scales provided by the OECD within the international database. The scales are respectively obtained from the question items IC011, referred to the frequency of use of digital devices at school for several activities, and IC150, referred to the school instructional weekly time spent using digital devices in the main subjects. The use of these variables allows to capture the intermediate step in the transformation of resources into educational outputs (Mancebón et al., 2012). On the one hand, it appears that there are countries with low frequency of ICT usage, but high amount of ICT instructional time, such as Bulgaria and Latvia. On the other hand, Iceland shows high values of both variables, while Ireland reports low values for both variables.

Finally, the socioeconomic background of students (ESCS, aggregated at school level), the shortage of school resources (using the OECD index EDUSHORT), and the percentage of students enrolled in a general track (using the variable ISCEDO), are considered as environmental (external) factors. This EDUSHORT index accounts for four dimensions: lack of educational material; inadequate or poor quality educational material; lack of physical infrastructure; inadequate or poor quality physical infrastructure. The higher the value, the poorer the school infrastructures. The inclusion of the socioeconomic background of the students as an environmental variable is in line with previous literature (see Mergoni and De Witte, 2021b). The moderating effect of such environmental variables has been investigated in previous research, which demonstrated the relevance of their integration in efficiency models (De Witte & Kortelainen, 2013). The descriptive analysis shows that the average school ESCS is homogeneously distributed among the countries in our sample, with the exception of Turkey, characterized by the lowest average ESCS, and Iceland, characterized by the highest average ESCS. As for the shortage of school resources, the countries with the smallest shortage are Turkey and Switzerland.

Table 2: Descriptive statistics for the variables included in the analysis, by country

Country	Size	Teach_ratio		Computer_ratio		ICT_usage		ICT_class		Math		Reading		Science		ESCS		Shortage		Track	
		mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
BEL	212	1.12	0.07	1.18	0.17	2.60	0.45	2.51	0.32	514.71	61.26	500.67	63.68	508.54	61.13	0.12	0.46	−0.06	0.90	0.57	0.41
BGR	109	1.09	0.03	1.09	0.05	3.22	0.39	2.73	0.41	429.44	64.43	414.29	69.91	417.25	65.14	−0.31	0.63	−0.39	0.90	0.45	0.48
CHE	207	1.09	0.038	1.19	0.19	2.56	0.40	2.45	0.39	512.78	54.85	479.91	62.84	491.21	58.32	−0.01	0.48	−0.48	0.83	0.84	0.35
CZE	303	1.08	0.03	1.15	0.10	2.81	0.45	2.42	0.35	505.32	68.15	496.44	73.53	503.94	71.88	−0.15	0.52	0.15	0.80	0.68	0.46
DNK	208	1.08	0.039	1.12	0.15	3.36	0.28	4.31	0.34	499.6	39.19	491.36	42.30	481.97	42.85	0.39	0.40	−0.34	0.86	1	0
ESP	907	1.10	0.10	1.11	0.13	2.61	0.42	2.65	0.46	488.52	36.91	480.70	40.91	489.03	35.83	−0.09	0.55	0.12	1.06	0.99	0.03
EST	22	1.10	0.04	1.12	0.09	2.57	0.39	2.72	0.29	519.04	43.11	519.86	48.89	525.96	47.01	−0.02	0.44	0.12	0.84	0.99	0.07
FIN	161	1.09	0.02	1.12	0.09	2.91	0.21	2.81	0.29	507.88	26.39	521.26	32.17	520.62	29.57	0.29	0.32	0.07	0.79	1	0
FRA	186	1.09	0.04	1.21	0.19	2.67	0.3	2.52	0.29	482.59	73.17	479.72	76.05	480.94	72.54	−0.13	0.55	−0.28	0.94	0.79	0.32
GRC	200	1.12	0.05	1.09	0.07	2.67	0.56	2.35	0.40	443.30	56.16	447.59	69.21	444.81	56.99	−0.21	0.58	0.53	1.00	0.87	0.33
HRV	168	1.11	0.03	1.12	0.08	2.67	0.35	2.41	0.24	460.91	54.00	474.86	58.06	468.78	56.93	−0.25	0.37	0.79	0.96	0.31	0.42
HUN	19	1.11	0.06	1.14	0.10	2.59	0.50	2.42	0.42	466.69	75.59	461.73	78.73	465.82	78.03	−0.27	0.73	0.39	0.95	0.87	0.34
IRL	119	1.08	0.02	1.13	0.07	2.33	0.33	2.33	0.37	496.49	33.37	514.53	37.61	492.09	36.78	0.09	0.38	0.19	1.02	0.99	0.02
ISL	103	1.12	0.08	1.19	0.18	2.98	0.29	3.18	0.54	487.44	31.04	466.05	35.16	465.59	31.08	0.37	0.37	−0.31	0.86	1	0
ITA	432	1.146	0.09	1.14	0.14	2.81	0.42	2.67	0.37	487.02	64.81	471.25	66.16	467.85	61.21	−0.27	0.47	0.25	0.97	0.46	0.49
LTU	357	1.12	0.06	1.15	0.11	2.88	0.48	2.73	0.39	463.17	59.85	450.34	65.76	460.07	59.66	−0.13	0.55	0.07	0.74	0.97	0.16
LUX	38	1.12	0.03	1.20	0.17	2.67	0.30	2.39	0.36	485.10	56.99	471.13	61.81	480.91	59.22	0.12	0.64	−0.36	0.78	0.76	0.26
LVA	271	1.114	0.048	1.109	0.071	3.041	0.388	2.580	0.316	485.804	42.83	465.741	48.759	477.490	43.313	−0.14	0.484	−0.157	0.811	0.992	0.086
MLT	47	1.160	0.066	1.127	0.086	2.304	0.481	2.637	0.307	481.137	48.229	457.14	56.880	466.403	49.494	0.181	0.460	−0.428	0.766	1	0
POL	236	1.162	0.121	1.154	0.151	2.838	0.446	2.494	0.328	519.741	46.264	515.187	50.311	513.187	48.116	−0.148	0.451	−0.163	0.884	0.983	0.129
SVK	304	1.083	0.024	1.142	0.107	2.861	0.559	2.709	0.382	481.313	63.576	449.802	67.086	457.866	61.057	−0.224	0.534	0.420	0.888	0.758	0.428
SVN	240	1.20	0.187	1.289	0.279	2.657	0.469	2.306	0.332	491.481	60.392	478.52	63.974	490.313	60.589	−0.043	0.463	−0.069	0.916	0.43	0.496
TUR	178	1.08	0.04	1.059	0.070	2.552	0.374	2.931	0.457	449.389	67.410	460.942	67.534	464.051	64.132	−1.167	0.749	−0.539	0.911	0.681	0.460

Note : The table includes the descriptive statistics for the variables used for the analysis. The teacher and the computer ratio are the inputs, the ICT usage and ICT class are the intermediate measures (these are standardised indicators elaborated by PISA), the score in math, reading and science are the outputs. The exogenous variables are ESCS and Shortage (indicators for the students' socio-economic status and shortage of school resources, respectively), and the proportion of students enrolled in the general track. The column size indicates the number of schools representing the country. The statistics are reported at country level, despite the analysis is at school level. The sample include 23 countries: BEL = Belgium, BGR = Bulgaria, CHE = Switzerland, CZE = Czech Republic, DNK = Denmark, ESP = Spain, EST = Estonia, FIN = Finland, FRA = France, GRC = Greece, HRV = Croatia, HUN = Hungary, IRL = Ireland, ISL = Iceland, ITA = Italy, LTU = Lithuania, LUX = Luxembourg, LVA = Latvia, MLT = Malta, POL = POland, SVK = Slovakia, SVN = Slovenia, TUR = Turkey

4 Results

4.1 The efficiency of schools and the role of ICT: findings from the robust network DEA

The results of the robust efficiency estimations are reported in Table 3 and highlight three main findings. First, the average overall school efficiency is homogeneous among the European countries and the value is 0.58, with a minimum in Luxemburg (0.51) and a maximum in Finland (0.68). This indicates that schools may significantly increase their students' PISA scores by better using the ICT and human resources already available. Despite it was not possible to test for this, it is reasonable to suspect that a major role in the educational activity of transforming ICT resources in students' achievement is played by the teacher. Therefore, training program might be effective in increasing the overall schools' efficiency, especially in countries with a high average teacher age or with teachers particularly technologically untrained.

Second, the results suggest that the process of transforming ICT instructional time into student achievement is the major source of (in)efficiency (or a driver of (in)efficiency) for the overall process and this is relatively more important than the efficiency in transforming resources into instructional time to influence the overall efficiency scores. This conclusion is supported by three evidences. First, results show that the first stage efficiency is, in most countries, higher than the second stage efficiency.[3] Second, the correlation between the overall and second stage efficiency (Table 3, Column 2) is, in general, higher than the correlation between the overall and the first stage efficiency (Table 3, Column 1). A positive correlation between the overall efficiency and the second stage efficiency indicates that the schools that are efficient in using their resources to obtain high PISA scores (overall) are also efficient in using ICT mediated instructional time (second stage), which can be then considered a driver for efficiency. In other words, the ability of exploiting ICT usage in an educational sense is an important channel to explain the school efficient use of resources. Third, most countries are characterized by a weak negative correlation between the overall efficiency and the first stage efficiency.[4] On the one hand, this evidence confirms again that the main driver of the overall efficiency is the second stage; on the other hand, it indicates that schools that are efficient in the process of using ICT given their level of resources, are not as efficient in the use of ICT for educational purposes, suggesting that is not the use of ICT per se that provides higher educational outcomes.

In line with this last finding, a third evidence that emerges from the analysis is that other channels, besides ICT, are also relevant in determining the schools' efficiency. This hypothesis is confirmed by the negative correlation, for all countries, between the first and second stage efficiency, i.e., between the ability of the schools of exploiting the resources to provide ICT use and the ability of the school of exploiting the ICT use to obtain high PISA. On the one hand, this negative correlation indicates that the schools that concentrate their effort in the channel of ICT, might then fail to exploit ICT efficiently to achieve educational results. On the other hand, it reveals the presence of schools that are not very efficient in providing ICT instructional time given their resources, but are more efficient in the exploitation of ICT towards better educational achievement. The relative quality of school resources is a possible explanation of these two mechanisms. It can be supposed that schools that have not many resources at their disposal focus on the channel of ICT delivery in terms of instructional time. Schools in the second case, instead, might have at their disposal better quality educational resources, therefore do not need to concentrate their effort in the delivery of ICT instructional time to be efficient. If

[3] An average second stage efficiency higher than first stage efficiency characterizes all the country in the sample, except for Greece, Hungary, Ireland, and Malta.

[4] Exceptions are Belgium, Denmark, Spain, France, Finland, Island, Malta, Poland, Slovenia and Turkey, for which there is a positive correlation between the overall and first stage efficiency.

true, this would raise serious questions about the effectiveness of the teaching practices adopted by the relatively richer schools.

4.2 The role of external variables: findings from the conditional network DEA

To further test the presence of other channels in explaining schools' efficiency, a conditional analysis has been implemented. In particular, the analysis controls for the quality of school resources, approximated by the resource shortage and the socioeconomic status of the students. The results, reported in table 4, show that when accounting for quality, the efficiency scores of the first and second stage become similar and the negative correlation between the two stages is not statistically significant. The strong variation of the results confirms the importance that quality of resources and context play as determinants of schools' efficiency. The relationship between efficiency and contextual factors is further investigated through a non-parametric regression (see Figure 3), where the ratio of the robust over the conditional efficiency is the dependent variable. The higher the conditional efficiency with respect to the robust (therefore the lower the ratio robust over conditional), the more the conditional variables have a negative influence on the ability of schools of being efficient; a lower conditional score indicates instead favourable conditional variables. In the regression analysis this is reflected by positive or negative slopes, which indicate, respectively, favourable or unfavourable variables. In line with the literature, a better socioeconomic background of the students and less resource shortage are favourable conditions for the overall school efficiency, despite these effects are not particularly significant. On the contrary, being in a school with a high percentage of students in a general track is unfavourable, despite not significant. This indicate that possibly the use of ICT is more efficient in schools where students are required to learn more applied skills.

An important point must be clarified and emphasized here. The analysis does not highlight that better students' background, resources, and the kind of track lead to higher test scores, something that is already well acknowledged in the literature. Instead, the findings indicate that these elements affect the way in which the schools operate, at any level of performance, so affecting their efficiency in turn.

5 Concluding remarks and policy implications

This paper explores the relationship between ICT resources, their use in terms of instructional time and schools' efficiency in an international perspective, by employing data from 23 European countries extracted from the 2018 edition of the OECD PISA. Efficiency is calculated by means of DEA, a non-parametric technique widely used in the educational research domain (De Witte & López-Torres, 2017). In particular, an innovative network-DEA structure is used to provide greater insights into the sources of schools' (in)efficiency (C.-T. Tran, 2021). The network structure allows to consider that the role of ICT resources in the schools' production process for developing students' knowledge might be mediated by the ICT usage (i.e. by the amount of ICT mediated instructional time). The first stage defines efficiency as the ability of schools to transform resources, in terms of teachers and ICT, for obtaining ICT-mediated instructional time; the second stage evaluates the ability of using ICT within the educational activities for improving students' skills and competences. The structural differences across schools in different countries are controlled using a local frontier for the estimation of country-specific efficiency scores. Also, the potential role of contextual variables on schools' efficiency is explored through a conditional efficiency model – where the contextual factors are defined and measured as the

Table 3: The robust efficiency of schools, by country

	Overall	Stage1	Stage2	CORR1	CORR2	CORR3
BEL	0.568	0.800	0.726	0.177	0.590	−0.670
BGR	0.544	0.798	0.703	−0.245	0.781	−0.774
CHE	0.598	0.805	0.759	0.055	0.620	−0.729
CZE	0.580	0.803	0.742	−0.208	0.750	−0.777
DNK	0.675	0.870	0.784	0.148	0.522	−0.752
ESP	0.528	0.738	0.737	0.172	0.387	−0.798
EST	0.612	0.818	0.765	−0.176	0.643	−0.846
FIN	0.676	0.824	0.831	0.069	0.449	−0.847
FRA	0.641	0.848	0.766	0.106	0.754	−0.558
GRC	0.552	0.771	0.741	−0.382	0.766	−0.855
HRV	0.575	0.803	0.731	−0.067	0.725	−0.714
HUN	0.567	0.785	0.741	−0.045	0.735	−0.678
IRL	0.549	0.724	0.782	−0.064	0.505	−0.862
ISL	0.590	0.794	0.760	0.227	0.266	−0.853
ITA	0.561	0.799	0.721	−0.123	0.709	−0.740
LTU	0.570	0.808	0.722	−0.040	0.681	−0.705
LUX	0.513	0.817	0.647	−0.181	0.659	−0.805
LVA	0.597	0.799	0.764	−0.083	0.607	−0.811
MLT	0.543	0.749	0.738	0.274	0.648	−0.527
POL	0.557	0.789	0.728	0.080	0.426	−0.823
SVK	0.547	0.807	0.697	−0.242	0.725	−0.806
SVN	0.576	0.775	0.758	0.363	0.584	−0.518
TUR	0.575	0.839	0.702	0.027	0.635	−0.723

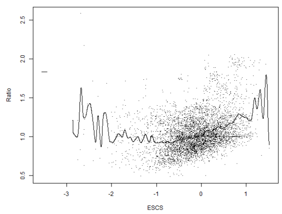
Note : Column 1 contains the overall efficiency scores obtained from the robust centralized network model. The robust overall score can be decomposed in the efficiency of the first stage, reported in column 2, and the efficiency of the second stage, reported in column 3. Column 4 reports the correlation between the overall efficiency and the stage 1 efficiency, column 5 reports the correlation between the overall efficiency and the stage 2 efficiency, column 6 reports the correlation between stage 1 and stage 2 efficiency.

Table 4: The conditional efficiency of schools, by country

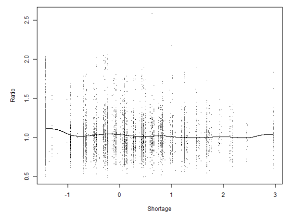
	Overall	Stage1	Stage2	CORR1	CORR2	CORR3
BEL	0.832	0.924	0.904	0.528	0.715	−0.210
BGR	0.888	0.954	0.933	0.500	0.787	−0.138
CHE	0.847	0.937	0.908	0.413	0.737	−0.309
CZE	0.826	0.916	0.906	0.487	0.711	−0.263
DNK	0.848	0.933	0.911	0.517	0.732	−0.202
ESP	0.692	0.843	0.831	0.505	0.567	−0.413
EST	0.850	0.933	0.914	0.508	0.723	−0.225
FIN	0.872	0.938	0.932	0.549	0.637	−0.293
FRA	0.891	0.957	0.933	0.461	0.813	−0.139
GRC	0.831	0.923	0.903	0.478	0.749	−0.220
HRV	0.865	0.942	0.920	0.500	0.723	−0.235
HUN	0.850	0.928	0.917	0.541	0.736	−0.167
IRL	0.899	0.954	0.945	0.588	0.649	−0.234
ISL	0.837	0.912	0.920	0.646	0.650	−0.156
ITA	0.771	0.898	0.865	0.400	0.697	−0.373
LTU	0.802	0.909	0.885	0.519	0.717	−0.219
LUX	0.927	0.966	0.959	0.752	0.772	0.165
LVA	0.830	0.921	0.904	0.477	0.736	−0.240
MLT	0.954	0.977	0.976	0.767	0.682	0.056
POL	0.806	0.908	0.891	0.564	0.703	−0.184
SVK	0.790	0.914	0.870	0.424	0.730	−0.304
SVN	0.821	0.909	0.905	0.627	0.669	−0.151
TUR	0.715	0.887	0.812	0.384	0.756	−0.304

Note : Column 1 contains the overall efficiency scores obtained from the conditional centralized network model. These scores can be decomposed in the conditional efficiency of the first stage, reported in column 2, and the conditional efficiency of the second stage, reported in column 3. Column 4 reports the correlation between the overall efficiency and the stage 1 efficiency, column 5 reports the correlation between the overall efficiency and the stage 2 efficiency, column 6 reports the correlation between stage 1 and stage 2 efficiency.

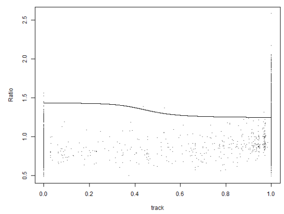
Figure 3: Non parametric regression to explain the ratio of the conditional over the robust efficiency



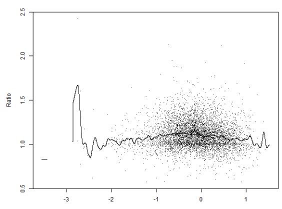
(a) Effect of the socioeconomic background of the student on the overall efficiency of the school



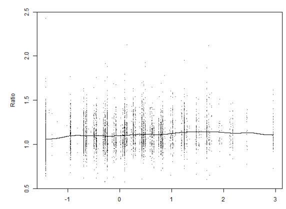
(b) Effect of resources' shortage of school on the overall efficiency of the school



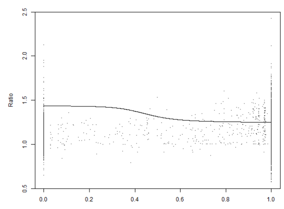
(c) Effect of the school track on the overall efficiency of the school



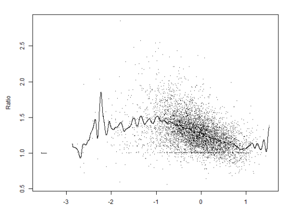
(d) Effect of the socioeconomic background of the student on the first stage efficiency of the school



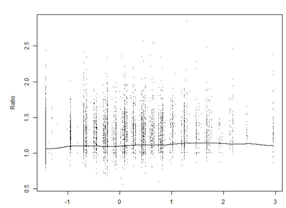
(e) Effect of resources' shortage of school on the first stage efficiency of the school



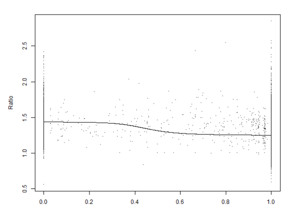
(f) Effect of the school track on the first stage efficiency of the school



(g) Effect of the socioeconomic background of the student on the second stage efficiency of the school



(h) Effect of resources' shortage of school on the second stage efficiency of the school



(i) Effect of the school track on the second stage efficiency of the school students' socioeconomic background, the shortage of educational resources and the percentage of students enrolled in a general track.

The findings of this paper can be summarized in three main messages. First, there is ample room to improve the efficiency of schools. In an international perspective, this result corroborates the evidence presented by Agasisti and Zoido (2018). In the baseline model presented here, the output of schools (the average test scores in reading, math and science) can be improved by almost 50% without increasing the available ICT resources. Second, it appears that the main source of (in)efficiency is related with the transformation of the ICT instructional time in student learning, much more than with acquiring ICT and human resources per se. Third, the conditional analysis reveals that there are external factors, out-of-the-school control, that play an important role in determining school's production process and these factors account approximately for 30% of the measurable schools' inefficiencies.

Previous studies on the role of ICT in K-12 education show inconsistent evidence and recognize only a moderate positive impact of ICT on student achievement (De Witte & Rogge, 2014; Fernández-Gutiérrez et al., 2020; Hu et al., 2018; Skryabin et al., 2015). In particular, they highlight that ICT resources alone are not sufficient to improve the performance of students (Basri et al., 2018) and additional ICT resources have a negative impact on schools productivity (Feliciano et al., 2021). A possible explanation, which is line with our findings, is that the use of ICT in schools is explained more by teachers' usage rather than by ICT infrastructure (Gil-Flores et al., 2017). Besides, positive attitudes of teachers towards ICT are associated with better results, showing that quality over quantity might be the key (Petko et al., 2017; Scherer et al., 2018). In line with this idea, De Witte et al. (2015) and Mehrvarz et al. (2021) showed that digital competences are crucial to lead to higher educational outcomes.

The results presented in this paper are important from the perspective of educational policies. The process of improving students' performance with the available resources is far to be satisfactory. The attention of policy makers must remain concentrated on challenging school administrators and teachers to keep searching new ways of employing their resources in the best way, as oriented towards students' learning. For example, while this paper treats the quality of educational resources as an external (contextual) factor, the role of school principals in using money for better equipping schools should be strengthened – this can also be intended as a possible policy implication in the direction of more autonomy for schools. In addition, the role of ICT is questioned in the light of this paper's findings. The last years have been characterized, in many countries, by substantial investments in ICT facilities (both software and hardware) for schools, with the explicit assumption that they could modernize the educational activities and improve students' results. This is not always the case, though. The findings here suggest that part of the schools' inefficiencies stems exactly from the inability of a proper ICT use for learning. This unsatisfactory use of technology can be due to the difficulty in matching students and teachers' skills. On the one hand, some teachers might not be properly trained or motivated in using ICT; on the other hand, students' proficiency in ICT could also be heterogeneous. In particular, it seems that inequality can increase if students with higher socioeconomic status might have an advantage in the use of ICT both for their higher initial skills and for the availability of more trained teachers. The next years should be characterized by a better channelling of ICT resources, accompanying the availability of new hardware and software with teachers and students' training for ensuring their use directed towards learning results. In the context of post-COVID schooling, this indication appears as a key priority for policymakers. In the case of countries belonging to the European Union, the digitalization of educational systems is also considered among the priorities for the Recovery and Resilience Facility.

This research also paves the way for future extensions, depending upon data availability. On the one side, more detailed information about the ICT resources and their use would allow researchers to characterize the relationship between this factor and schools' productive process and efficiency. Data collected by OECD PISA, although rich, are still partial – for example, they do not explore in detail the use of ICT for specific teaching practices. On the other side, the collection of more detailed variables about schools' contextual factors – like the level of technological development of the territory where the school operates, the teachers, expertise with ICT, teachers propensity towards technology, etc. – can help disentangling the efficiency from external influences in a more appropriate way.

A final key message can be derived from this paper. Schools' efficiency can be improved, and ICT usage plays a role in this picture. The improvement of schools' efficiency will be beneficial for students, their families, and the whole society. Better understanding the mechanisms behind the performance of schools is then important, as it is conceiving better policies for this purpose.

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