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Two-stage super-efficiency model for measuring efficiency of education in South-East Asia

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Abstract
This paper aims to measure the efficiency of schools in six South-East Asian countries, taking into account the impacts of information and communication technologies (ICT). The educational institutions of South-East Asia are very dynamic; and to increase their competitiveness at international level, they need to manage their resources in an efficient way. We propose a two-stage super-efficiency model for measuring their efficiency, using 2018 PISA data. In the first stage, the non-parametric data envelopment analysis super-efficiency model is used to rank the schools in this region. Then, a second-stage analysis based on a bootstrapped quantile regression is performed to identify the factors that potentially influence efficiency. We analyze four different scenarios depending on the output considered. In the first stage of the analysis, Singapore has the best performance among the other countries in all scenarios. In the second stage, our results show that ICT is statistically significant as a determinant of efficiency in terms of the ratio of computers connected to the internet. However, the integration of ICT in education is mainly influenced by the socio-economic and educational factors of the analyzed countries. Moreover, concerning the other factors, the lower efficiency schools benefit more from the number of female students than higher efficiency schools. The reverse happens for the proportion of certified teachers.

Keywords Bootstrapped quantile regression · Education · South-East Asia · Super-efficiency · Slacks-based measure

JEL Classification C61 · C81 · I21

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1 Introduction

This paper presents a study which aims to measure efficiency of schools in South-East Asia by means of a two-stage super-efficiency model. South-East Asia is one of the most competitive, enterprising, and vibrant education scenes in the world and it is found in as one of the fastest-growing regions among rising economies (Asian Development Bank 2011; World Bank 2010). In this geographical area, there are eleven countries: Brunei Darussalam, Cambodia, East Timor, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Thailand, Vietnam. Ten of these are members of the Association of Southeast Asian Nations (ASEAN), while East Timor is an observer country.[1] The analyzed region covers more than 4.5 million km^2 with a combined total population of more than 680 million people (May 2022 est.), about 8.5% of the world's population. The number of populations varies from the fourth world populous country like Indonesia with more than 270 million people to the least populace country like Brunei Darussalam (about 430 thousand people). The region is culturally and ethnically diverse, with hundreds of languages spoken by different ethnic groups. In addition, ASEAN is a major global hub of manufacturing and trade, as well as one of the fastest-growing consumer markets in the world. Eight ASEAN states (i.e., Singapore, Thailand, Malaysia, Indonesia, Myanmar, Laos, Cambodia, Vietnam) are among the world's top-performing economies in 2018, indicating favorable long-term prospects for the region (Woetzel et al. 2018). Furthermore, the ASEAN Secretariat plans that the regional body will grow to become the world's fourth largest economy by 2030 (Gronewold 2019).

The qualities of the education system in South-East Asia are of great interest, which is in line with these economic trends. In particular, academics have made assumptions about the high levels of student achievement in this region, the recent changes in educational regulations, and the current policy debates in these nations (Cheng 1999). The majority of decision-makers and the general public in these nations are aware of how crucial education is to the advancement of their societies, and they have taken significant steps to strengthen and extend their educational institutions. Regardless of the varied levels of development across the nations in this region, promoting quality and equity in education is a shared policy. The region's intrinsic diversity encourages the establishment of educational standards for the region's relatively young and expanding population that are both globally competitive and regionally anchored.

Expectations from the government, the public, the media, and other stakeholders encourage educational institutions to manage their resources more effectively; as a result, countries in South-East Asia are currently coming under increasing pressure to boost productivity and raise the standard of their operations. However, comparative studies in—especially in education—that critically examine this region has yet to be achieved (Symaco and Chao 2019); and despite the promising analysis of educational issues in one of the most compact regions in the world, published studies about measuring efficiency in the education sector in this region is quite limited. Relying on the

[1] Founded in 1967, ASEAN is a political and economic union of ten member countries and one observer country located in Southeast Asia, which promotes intergovernmental cooperation and facilitates economic, political, security, military, educational, and sociocultural integration between its members and countries in Asia–Pacific.

finding of the literature review described in the next section, there are few studies measuring efficiency of education in South-East Asia in a quantitative way. Therefore, this study attempts to close the gap in the literature by conducting a cross-country analysis of measuring efficiency in education in this region.

There can be several methodologies to measure efficiency in education belonging to parametric or non-parametric techniques. Stochastic frontier analysis (SFA) is a parametric approach that has been long criticized for relying on restrictive assumptions concerning the functional form and the distribution of the error term. On the other hand, data envelopment analysis (DEA), a non-parametric technique, relaxes those assumptions, but it suffers from being highly vulnerable to potential outliers and measurement error since every decision-making unit (DMU) is related to the most efficient DMUs. A simple idea to correct for potential outliers was proposed by Andersen and Petersen (1993) in which it leads to the concept of super-efficiency. The idea is to leave out one DMU to be evaluated from the solution set. This model allows the efficient DMUs to have efficiency scores of more than one (note that in the traditional DEA, the efficiency score is bounded from zero to one). However, the Andersen and Peterson's model under the variable returns-to-scale (VRS) assumption suffers from having no feasible solution under certain condition. To overcome this issue, the slacks-based measure (SBM) of super-efficiency in DEA under the VRS assumption has been introduced and it is proved that this model is always feasible and has a finite optimum (Cooper et al. 2006).

Taking into account all these methodological considerations and the fact that South-East Asia is characterized by heterogeneity, we propose a two-stage model to investigate the efficiency of the education systems in South-East Asia. In the first stage, an SBM of super-efficiency model in the DEA under the VRS assumption to the study of efficiency is applied. Countries in South-East Asia indeed have varied political, cultural, socio-economic and environmental settings. For example, Singapore is an island state, while in contrast, Indonesia has a huge population and large geographical area. According to the World Bank classification, Brunei and Singapore are classified as high-income countries; Malaysia and Thailand are upper-middle income countries, while Indonesia and the Philippines are classified as lower-middle income countries. On the other hand, Cambodia, Laos, Myanmar, East Timor, and Vietnam are rated as low-income countries. Thus, the majority of the countries in the region are developing nations. Except for Thailand, all other countries in the region have a colonial history, and generally their political, economic and education systems are influenced by their colonial heritage. Therefore, the potential outliers in terms of educational efficiency might exist. This study, then, implements the super-efficiency model—in particular, the SBM of super-efficiency model—to perform cross-country analysis of efficiency measurement of education in South-East Asia region. However, one of the shortcomings of the DEA approach is that it cannot investigate factors that might influence efficiency in education of South-East Asia, the so-called the determinants of efficiency. Therefore, in the second stage of analysis, this study applies a bootstrapped quantile regression to examine the influence of the determinants of efficiency. Before proceeding into the second stage, we perform "separability condition test" (Daraio et al. 2018) to test the assumption that the determinants of efficiency cannot affect the support of input and output variables in the first stage (Simar and Wilson 2007); and show that there is no evidence against separability of the determinants of efficiency.

The paper's contributions are:

1. The use of the bootstrapped quantile regression for investigating the influence of determinants of efficiency at the second stage of our analysis.

Previous studies used the classic regression analysis with ordinary least square (OLS) estimation to examine the influence of determinants of efficiency (see the literature review described in the next section). However, this procedure has several drawbacks. First, it cannot answer an important question: "Do the determinants influence efficiency levels differently for high-efficient schools and for those with low or average efficiency levels?" (Nwaogbe et al. 2018). The OLS estimates the mean (or the expected value) rate of change of the dependent variable as a conditional function of one or several independent variables. This feature can lead to inaccurate estimates of coefficients or the omission of important relationship. On the other side, a quantile regression extends this estimation to any part of the dependent variable's distribution, i.e., to any selected quantile (or percentile). This facilitates a clearer interpretation of the relationship between variables that may otherwise have weak or no relation (Arshad et al. 2018). As such, quantile regression allows the simultaneous study of changes in specific portions of the distribution of the dependent variable to independent variables independently of the change and variability experienced by the rest of the distribution. This allows comparison of how some percentiles of the efficiency levels may be more affected by certain determinants of efficiency than other percentiles. Moreover, as mentioned by Simar and Wilson (2007), the OLS regression procedure is flawed by the fact that usual inference on the obtained estimated of the regression coefficient is not available. For this reason, they proposed a bootstrap algorithm to obtain more accurate inference. In addition, the bootstrap procedure can be used to correct the biases resulting from the correlation between the inputs or outputs of the first stage and the regressors of the second stage. Finally, one should also consider for the skewness of those efficiency scores (recall that the distribution of the efficiency score is not symmetric, see Gajewski et al. 2009; Santín and Sicilia 2017; Sowlati and Paradi 2004); thus, it is suggested to use the quantile regression which relies on the conditional quantiles rather than the conditional means as in OLS. As discussed in Angrist et al. (2006), quantile regression can explain changes in distribution shape and spread, i.e., the skewness of the efficiency scores. Taking all these together, this study uses the bootstrapped quantile regression in the second stage of analysis. Due to these benefits of the bootstrapped quantile regression that is more robust to outliers than the OLS regression, to account for the issue of bias-correction (via bootstrap), as well as the skewness of efficiency scores, it is suggested that this procedure would present more insightful information compared to the conventional one.

2. The inclusion of ICT-related variables as inputs and determinants of efficiency.

Previous studies investigating the education systems in South-East Asia did not incorporate ICT into their model; thus, the role of ICT has not been yet investigated. In the education sector, the application of ICT has increased substantially over the last few years (Comi et al. 2017; Falck et al. 2018) as many countries have been investing their resources in ICT infrastructure for educational purposes. There are two opposite sets of observations in the literature about the influence of ICT on the efficiency of education (De Witte and Rogge 2014). On the one hand, some scholars found that ICT could reduce educational costs. Other advantages are improving the delivery of education and the learning process, the presence of greater flexibility and autonomy for the students' learning, as well as supporting more interaction and a reduction in the teachers' workload (Grimes and Warschauer 2008; Lei and Zhao 2008; Venable et al. 2011). On the other hand, when ICT is not well integrated in the curriculum, due to pedagogical barriers, it might hinder students from learning (Fu 2013). There are also some barriers that obstruct the use of ICT in education from the teacher perspective, such as a lack of teacher collaboration and pedagogical support, a lack of in-service training on the use of ICT, insufficient time to master new educational software or to integrate ICT during a class period, limited knowledge and experience of ICT in teaching contexts, as well as several technical problems related to ICT in the classroom that frequently happened. Moreover, when the teachers use ICT in the classroom, it might negatively distract the students. Due to this inconclusive explorative finding, the question to be answered is: "has this investment paid off in terms of higher efficiency?" This study then attempts to investigate whether ICT has influence of school's efficiency or not.

3. Lastly, this study can be considered as the first study which assesses the efficiency across country in South-East Asia.

As the literature review discussed in the next section, the previous studies only focused on one specific country in the region, while in this study, a more detailed analysis is provided in cross country level. Literature comparing the efficiency of schools across country is still in its infancy. Despite the inherent appeal of international comparisons, studies comparing school performance across nations have only developed to a limited extent due to (i) a lack of trustworthy datasets and (ii) the significant variations in institutional (country-specific) contexts (Agasisti and Zoido 2019). Therefore, to overcome both of these limitations, this study uses the recent OECD PISA 2018 data, which is regarded as a reliable source of comparison for educational achievement around the world.

The remainder of this paper is structured as follows. In the next section, a literature review is conducted to present previous studies of the application of super-efficiency model in education sector. The methods used in this study are briefly described in Sect. 3, while data and variables used are shown in Sect. 4. The findings of this study are presented in Sect. 5; and finally, Sect. 6 concludes.

2 Literature review

This study aims to measure the efficiency of schools in South-East Asia by the means of two-stage super-efficiency model. Literature about measuring efficiency of education in South-East Asia is quite limited. As far as we found, there are few studies evaluating efficiency in education for South-East Asian countries with a quantitative analysis.

Castano and Cabanda (2007) evaluated the efficiency performance of Philippine Private Higher Educational Institutions using DEA and SFA over the period 1999–2003. Lavado and Cabanda (2009) measured the efficiency of provinces in the Philippines in utilizing public resources for health and education with budget constraints. Johnes and Virmani (2020) used data from the Young Lives study to evaluate the efficiency of education systems in four low- and middle-income countries: Ethiopia, India, Peru, and Vietnam. Using DEA, Salcedo (2020) evaluated the performance efficiency of the teacher education programs in seven campuses of the Pangasinan State University in Philippine from academic year 2012–2013 to 2014–2015. Le et al. (2021) investigated how well a province in Vietnam transforms the family expenditure in education into the achievements of students and suggest benchmarks for policies and investments of a provincial government on how it can improve the education system. They used inverse optimization in DEA-based benchmarking to accomplish the objective. The main features of the aforementioned studies are summarized in Table 1.

Next, this study also extends one stream of literature of the application of two-stage super-efficiency model in the education sector. Table 2 summarizes the aspects analyzed in the reference papers that propose two-stage super efficiency models in the education sector.

Zhang et al. (2022) examined the influence of the innovation ability of universities (IAU) on the efficiency of university–industry knowledge flow and investigated whether the level of provincial innovative agglomeration moderates the relationship between IAU and the efficiency of the university– industry knowledge flow. This study used the radial DEA model allowing for super-efficiency to measure knowledge research efficiency and knowledge transformation efficiency and then studied the influencing mechanism of the two kinds of efficiency using the spatial Tobit model with panel data from 2008 to 2017. The sample included 104 universities in China. Zhang and Wang (2022) measured the knowledge innovation efficiency (KIE) and knowledge transformation efficiency (KTE) of industry–university–research knowledge flow using the super-efficiency radial DEA. In the second stage, the authors aimed to study the impact mechanism of innovative city pilot policy on the knowledge flow dual efficiency (i.e., KIE/KTE) by adopting spatial difference-in-difference (SDID). Zhou and Zhu (2021) measured the efficiency of scientific and technological (S&T) transformation in the Yangtze River Economic Belt, China, using the super-efficiency non-radial DEA. In the second stage, the authors used panel regression model to identify the influence of GDP, industrial structure, openness, human resources, scientific research projects, and international cooperation on the technology transformation efficiency of cities in that area. Chen and Shu (2021) explored S&T innovation performance of world-class universities in China from 2014 to 2019, based on the super-efficiency radial DEA model and the Malmquist index. In the second stage, the mixed OLS, fixed effect and random effect Tobit panel model was used to investigate the influence of the following determinants on the efficiency score: input factors quality index, the matching structure of scientific research elements index, the university and government relationship index, the industry-academia-research collaboration index, and the regional economic environment factor. Wohlrabe et al. (2019) assessed the efficiency of 50 *elite* US universities using DEA, free disposal hull, and two robust models:

Table 1 Articles measuring efficiency of education in South-East Asia

Articles	Methods	Level of analysis	Inputs	Outputs
Castano and Cabanda (2007)	DEA and SFA	University (in the Philippines)	Number of faculty members Property, plant, and equipment Operating expenses	Student enrollment Graduates per year Total revenue
Lavado and Cabanda (2009)	DEA	Province (in the Philippines)	Social services expenditure per capita	Life expectancy Functional literacy rate Combined primary and secondary enrollment rates
Johnes and Virmani (2020)	DEA	Cross-country (Ethiopia, India, Peru, and Vietnam)	The wealth index Household expenditure per capita Daily hours spent in class Daily hours spent in private study Highest grade completed Student age	Student's score in the Peabody Picture Vocabulary Test
Salcedo (2020)	DEA	Study program (teacher educa-tion programs in the Philippines)	For curriculum: Number of programs offered Total number of units in each program Total number of hours of teaching practice	For curriculum: Number of accredited programs Status of accreditation
Le et al. (2021)	DEA	Province (in Vietnam)	Inside expenditure pa-id by families for their children's education to educational institutions Outside expenditure paid by families for their children's education to educational institutions	Math score in National High-school Graduation Exam Vietnamese score in National High-school Graduation Exam

the order-m and order-α approaches. Only the two last approaches allow for super-efficiency. The authors then used the OLS regression analysis in the second stage. Türkan and Özel (2017) measured the efficiency of 43 state universities in Türkiye using the radial DEA; then, factors affecting efficiency are examined by Tobit and beta regression analysis. Agha et al. (2011) evaluated the relative technical efficiencies of academic departments at the Islamic University in Gaza during the years 2004–2006 using the radial DEA model allowing for super-efficiency. Further, multiple linear

Table 2 Articles using two-stage super-efficiency model in the education sector

Articles	Methods		Level of Analysis
	First stage	Second stage	
Zhang et al. (2022)	Super-efficiency radial DEA	Spatial Tobit model	University (in China)
Zhang and Wang (2022)	Super-efficiency radial DEA	Spatial difference-in-difference	University (in China)
Zhou and Zhu (2021)	Super-efficiency non-radial DEA	Panel regression model	University (in China)
Chen and Shu (2021)	Super-efficiency radial DEA	Mixed OLS, fixed effect and random effect Tobit panel model	University (in China)
Wohlrabe et al. (2019)	The order-*m* approach The order-α approach	OLS regression	University (in the US)
Türkan and Özel (2017)	Super-efficiency radial DEA	Tobit and beta regression model	University (in Türkiye)
Agha et al. (2011)	Super-efficiency radial DEA	Linear regression model	Departments at the Islamic University in Gaza
Lee (2009)	Super-efficiency radial DEA	Linear regression model	School (in Michigan, US)

regression was used to develop a relationship between super-efficiency and input and output variables. Lastly, Lee (2009) evaluated the competitive effect of charter schools on hosting school districts using the super-efficiency radial DEA and regression analysis to obtain a DID estimator to measure the effect of charter school enrollment on charter hosting districts.

According to the literature review, there are three methods to measure efficiency allowing for super-efficiency, i.e., the radial and non-radial DEA as well as the order-m and order-α approaches which belong to the partial frontier analysis (Amaral et al. 2022; Ferreira et al. 2018a, b; Wohlrabe et al. 2019). In this study, the two models of full frontier analysis (i.e., radial and non-radial DEA) are implemented to measure school's efficiency in South-East Asia. In the second stage, the bootstrapped quantile regression is used to examine the influence of determinants of efficiency. The bootstrapped quantile regression is proposed to handle issues of robustness to outliers, bias-correction, and skewness of efficiency scores as it has been discussed previously. Therefore, this study contributes to the literature of efficiency in education by extending the use of bootstrapped quantile regression in the second stage of two-stage super-efficiency model. Other than in education sector, the practices of bootstrapped quantile regression in the second stage of efficiency measurement (but not in the super-efficiency model) can be seen in studies on agriculture (e.g., Frýd and Sokol 2021), environmental or energy efficiency (e.g., Ibrahim et al. 2021; Moutinho et al. 2017; Qi et al. 2019), banking (e.g., Le et al. 2022), and aviation industry (e.g., Nwaogbe et al. 2018).

3 Methods

This study uses two-stage super-efficiency model which allows for a DMU to have efficiency score more than one. In the first stage, the non-parametric SBM-DEA model is used to measure efficiency of schools in South-East Asia. Then, the SBM of super-efficiency (SSBM) is applied to rank and differentiate the efficient schools, leading to the super-efficient schools. In the second stage, the bootstrapped quantile regression is applied to investigate the influence of determinants of efficiency. The use of the bootstrapped quantile regression is due to the benefits that this procedure is better to handle for the issues of bias-correction, skewness of the efficiency scores, and robustness to the outliers.

3.1 First stage of analysis

Data envelopment analysis (DEA) is a non-parametric technique to assess efficiency of a DMU. In particular, it measures the ability of a DMU to minimize inputs to produce given outputs or, equivalently, to obtain maximum outputs from given inputs (Kumbhakar and Lovell 2000). Consequently, a DMU is fully efficient if it produces the maximum possible outputs from a fixed level of inputs (in an output orientation), or if it uses the minimum possible inputs to produce a given level of outputs (in an input orientation). It is a non-parametric approach that requires very few assumptions in estimating efficiency compared to the parametric approach such as the SFA. In SFA, one has to define a functional form a priori and estimate the finite set of unknown parameters from the data. In addition, due to the use of maximum likelihood method, the distribution of inefficiency must be defined a priori. In DEA, these issues are not required. In addition, DEA can handle multiple outputs simpler that its parametric counterparts. DEA has been widely used in various applications, see e.g., Ferreira et at. (2016), Handayani et al. (2020), Pramono et al. (2019), Sari et al. (2018), Ulkhaq (2022, 2023a, b, 2024), Ulkhaq and Pratiwi (2022).

DEA can deal with both constant returns-to-scale (CRS), also called the CCR model after Charnes et al. (1978); and variable returns-to-scale (VRS), also called the BCC model after Banker et al. (1984). The CRS model is based on the assumption that constant return to scale exists at the efficient frontiers whereas VRS model assumes variable returns to scale frontiers. There are two different specifications of the radial DEA model, i.e., input-oriented (IO) and output-oriented (OO). In the IO model, DMUs minimize inputs while maintaining the same level of output. Conversely, in the OO model, DMUs maximize their level of outputs while keeping inputs constant. Basically, the difference is the ability that a DMU has to control input or output quantity. If it can control input, then the IO version is preferable, the opposite is true in the OO case. In this study, the OO model is employed because schools strive to maximize education outcomes and cannot easily reduce their inputs at least in the short term. This study uses the VRS model with the output-oriented approach. This model is widely used in the literature of measuring efficiency in education (see e.g., Agasisti 2014; Agasisti and Zoido 2019; Aristovnik 2013; Santín and Sicilia 2018).

There are two models of DEA, i.e., the "radial model" and "non-radial model". Historically, the radial measure, initially proposed by Charnes et al. (1978), was the first DEA model; whereas the non-radial model, represented by the slacks-based measure (SBM) model by Tone (2001) was a latecomer.[2] For instance, in the IO case, the radial model deals mainly with proportionate reduction of input resources. In other words, if the DMU has two inputs, this model aims at obtaining the maximum rate of reduction with the same proportion, i.e., a radial contraction in the two inputs that can produce the current outputs. In contrast, the non-radial model puts aside the assumption of proportionate contraction in inputs and aims at obtaining maximum rates of reduction in inputs that may discard varying proportions of original input resources. In this study, we use the SBM-DEA or the non-radial model due to the following reasons.

In the radial measure, an optimal solution is obtained if it satisfies two conditions, i.e., having efficiency score θ equals to 1 as well as having no slacks. Therefore, it is important to observe both the efficiency score and the slacks. Tone (1993) attempted to unify θ and slacks into a scalar measure. On the other hand, Charnes et al. (1985) developed the additive model of DEA which has no scalar measure. Tone (2001) then proposed the non-radial SBM model which deals with slacks of each input/output individually, independently, and integrate them into an efficiency measure. Moreover, the model has the important properties compared to the radial DEA as follows:

1. *Unit invariant* the measure is invariant with respect to the unit measurement of each input and output item.
2. *Monotone*: the measure is monotone decreasing in each input and output slack.
3. *Translation invariant* the measure is invariant under parallel translation of the coordinate system applied.
4. *Reference-set dependent* the measure is determined only by consulting the reference-set of the observed DMU.

To rank the efficient DMUs, the SBM of super-efficiency (SSBM) is applied (Tone 2002). Assuming the VRS environment, let us define a production possibility set $P \setminus (x_o, y_o)$ spanned by (X, Y) excluding (x_o, y_o) as

$$P_{SSBM-VRS} \setminus (x_o, y_o) = \left\{ (\overline{x}, \overline{y}) | \overline{x} \geq \sum_{j=1, \neq 0}^{N} \boldsymbol{\lambda}_j x_j,\ \overline{y} \leq \sum_{j=1, \neq 0}^{N} \boldsymbol{\lambda}_j y_j,\ \mathbf{e}\boldsymbol{\lambda} = 1,\ \overline{y} \geq \mathbf{0},\ \boldsymbol{\lambda} \geq \mathbf{0} \right\}, \tag{1}$$

where X is $m \times N$ matrix of inputs, Y is $s \times N$ matrix of outputs, $\mathbf{e}$ is a row vector with unity for all elements, and $\boldsymbol{\lambda}$ is the non-negative intensity vector. Further, a subset $\overline{P}_{SSBM-VRS} \setminus (x_o, y_o)$ of $P_{SSBM\text{-}VRS} \setminus (x_o, y_o)$ is defined as

$$\overline{P}_{SSBM-VRS} \setminus (x_o, y_o) = P_{SSBM-VRS} \setminus (x_o, y_o) \cap \{\overline{x} \geq x_o \text{ and } \overline{y} \leq y_o\}. \tag{2}$$

By the assumption of $X > 0$ and $Y > 0$, $\overline{P}_{SSBM-VRS} \setminus (x_o, y_o)$ is not empty.

[2] The additive DEA model can also directly measure non-radial inefficiency but is unable to report the efficiency of the unit in a scalar value. As such, the SBM is regarded as the successor of the additive model.

The SSBM with VRS-OO model is then defined as the optimal objective function (a DMU is said to be efficient if $\phi * = 1$) of the following

$$
\begin{aligned}
\phi^{*}_{SSBM-VRS-OO} &= \min \phi = \frac{1}{\frac{1}{s}\sum_{r=1}^{s}\frac{\overline{y}_r}{y_{ro}}} \\
\text{subject to } \overline{x} &\geq \sum_{j=1,\neq 0}^{N} \boldsymbol{\lambda}_j x_j \\
\overline{y} &\leq \sum_{j=1,\neq 0}^{N} \boldsymbol{\lambda}_j y_j \\
\overline{x} &= x_o \\
0 \leq \overline{y} &\leq y_o \\
\sum_{j=1,\neq 0}^{N} &\boldsymbol{\lambda}_j x_j \\
\boldsymbol{\lambda} &\geq \mathbf{0}
\end{aligned}
\tag{3}
$$

3.2 Second stage of analysis

This second stage of analysis is devoted to investigating the influence of determinants of efficiency by the means of bootstrapped quantile regression. The quantile regression was introduced by Koenker and Bassett (1978) and has become an increasingly important tool in statistical analysis. Suppose random variable y_i ($i = 1, 2, \ldots T$) is a random sample generated by a linear regression $y_i = \mathbf{x}_i$'$\boldsymbol{\beta}$ + $_i$, where y is the dependent variable, **x** represents the vector of independent variables, **β** is the corresponding vector of parameters, and ε_i is a random error whose conditional quantile distribution has a zero mean. The κth quantile, 0 < κ < 1 of the explained variables has the form of

$$
Q_{\kappa}(y_i|\mathbf{x}_i) = \mathbf{x}_i'\mathbf{b}, \tag{4}
$$

where **b** estimate shows the quantile regression κth and solves the minimization problem

$$
\arg\min_{b}\left[\sum_{i\in(i:y_i\geq \mathbf{x}_i'\mathbf{b})} \kappa\left|y_i - \mathbf{x}_i'\mathbf{b}\right| + \sum_{i\in(i:y_i<\mathbf{x}_i'\mathbf{b})} (1-\kappa)\left|y_i - \mathbf{x}_i'\mathbf{b}\right|\right] \tag{5}
$$

Since κ is equal to different values, different parameter estimations will be obtained. As Eq. (5) shows, the quantile regression minimizes the sum of absolute errors and, therefore, this method is more robust against outliers compared to the OLS (Guan 2003).

Next, in the bootstrapped quantile regression procedure, the methodological advantages of the quantile regression are amplified by the bootstrapping technique. The bootstrap is a robust statistical procedure which could be employed for a small sample analysis without relying on the error terms normality assumption. See e.g., Efron and Tibshirani (1986) for the procedure of the bootstrapping technique.

4 Data

The data is taken from the recent OECD PISA 2018 data. PISA is a triennial survey of 15-year-old pupils that assesses the extent to which they have acquired the key knowledge and skills essential for full participation in society (OECD 2019). The assessment focuses on proficiency in reading (language), mathematics, and science. First conducted in 2000, the major domain of study rotates between reading, mathematics, and science in each cycle. This study considers a sample of six countries, taken from the PISA 2018 edition, which are: Brunei Darussalam (BRN), Indonesia (IDN), Malaysia (MYS), the Philippines (PHL), Singapore (SGP), and Thailand (THA).

Apart from the assessment results, PISA also provides information that is potentially related to the assessment result, such as variables representing student background, school environment, or educational provision. This information comes from the responses given to different questionnaires. In this study, we only include student and school questionnaire. Since this study is conducted at the school level, the variables which are at student level have to be weighted using W_FSTUWT, the final student weight provide by PISA, to get school level variables.

In this study, we consider three different output variables measuring proficiency in mathematics (PVMATH), science (PVSCIE), and reading (PVREAD), respectively. These education outcomes are proxied by the weighted plausible values (PVs) provided by PISA—in this study, later it is called the PISA scores.

As inputs, four variables are used, i.e., (i) the (inverse) of student–teacher ratio (INVSTRATIO) which measures the quantity of human resources; (ii) the ratio of computers at school to the total number of students for educational purposes (COMPRATIO); (iii) the ratio of computers of the number of these computers that were connected to the internet (WEBCOMP); these latest two inputs act as indirect measures of schools' facilities related to ICT; and lastly (iv) to control for students' background, the index of school's economic, social, and cultural status (ESCS) is included.

ESCS is probably, just after student achievement scores, the most used variable in reports and in secondary analysis of data from PISA (Avvisati 2020). It helps to address relevant questions about educational opportunity and inequalities in learning outcomes. In PISA, ESCS is defined as a measure of students' access to family resources (financial capital, social capital, cultural capital and human capital) which determine the social position of the student's family (Avvisati 2020). It is a composite score based on three indicators: highest parental occupation, parental education, and home possessions. The rationale for using these three components was that the socioeconomic status has usually been seen as based on education, occupational status, and income (Sirin 2005; Willms and Tramonte 2019). As no direct income measure has been available from the PISA data, the existence of household items has been used as a proxy for family wealth. All three components were standardized for OECD countries and partner countries/economies with an OECD mean of zero and a standard deviation of one. ESCS has been widely known to explain the educational outcomes, see for example Crespo-Cebada et al. (2014), Ferrera et al. (2011), Perelman and Santín (2011a), Salas-Velasco (2020). The student–teacher ratio might affect the educational output as shown by Agasisti (2014), Agasisti et al. (2019), Agasisti and Zoido (2019). Lastly, the ICT-related variables have been used in several studies about measuring efficiency in education. For instance, COMPRATIO has been used in Zoghbi et al. (2013) to estimate the efficiency of higher education institutions in Brazil and Perelman and Santín (2011b) to investigate the performance of Spanish schools proxied by the PISA scores of mathematics and reading; while WEBCOMP has been used in Salas-Velasco (2020) to evaluate the performance of Spanish secondary schools. COMPRATIO is calculated as the number of computers for educational purposes divided by the total number of students in the school. WEBCOMP is calculated as the number of computers connected to the internet divided by the total number of computers for educational purposes.

After defining the outputs and inputs, the missing data is dropped (around 18%). At the end, the dataset comprises 1051 schools from 6 countries in South-East Asia. The average values of variables used in this study are shown in Table 3. The average PISA score in mathematics is 432.367, while in science and language are 412.792 and 435.5, respectively. Singapore has the highest scores in all domains, whereas the Philippines has the lowest scores in all domains. Since ESCS is scaled to have mean of zero and standard deviation of one across senate-weighted OECD countries, the fact that the mean of ESCS of these six countries is − 0.977 indicates that the economic, social, and cultural condition of the sampled schools is below the average values in the OECD countries. Singapore has the highest average value of ESCS. In terms of (inverse of) student–teacher ratio, the Philippines has the lowest score (i.e., 0.051, meaning that there is one teacher for every 20 students) while Brunei Darussalam has the highest score. Regarding the ICT-related variables, Singapore has both the highest ratios (i.e., 1.097 and 0.997 for COMPRATIO and WEBCOMP, respectively), while the Philippines has the lowest scores in both ratios.

Table 3 Average value of the variables

Variables	Total	BRN	IDN	MYS	PHL	SGP	THA
PVMATH	432.367	443.438	395.175	440.258	357.714	562.063	424.324
PVSCIE	412.792	422.414	384.233	414.144	345.105	544.099	395.753
PVREAD	435.500	446.364	408.920	437.512	362.726	544.757	432.394
INVSTRATIO	0.080	0.119	0.074	0.100	0.051	0.093	0.072
COMPRATIO	0.531	0.910	0.333	0.380	0.298	1.097	0.537
WEBCOMP	0.885	0.970	0.893	0.874	0.633	0.997	0.942
ESCS	−0.977	−0.161	−1.447	−0.778	−1.336	0.126	−1.287

Table 4 Descriptive statistics of the determinants of efficiency

Variables	Mean	Median	Std. Dev	Min	Max
PROP_GIRL	0.498	0.456	0.145	0	1
SCHSIZE	1,285.470	942	1,363.633	21	11,990
PROATCE	0.833	0.987	0.292	0	1
EDUSHORT	0.173	0.1	1.189	−1.421	2.96
STAFFSHORT	−0.043	0.0055	1.052	−1.455	4.044
COMPRATIO	0.531	0.357	0.545	0.008	8
WEBCOMP	0.885	1	0.249	0.01	1

As the determinants of efficiency, there are seven variables to be included. The first group of determinants is called school's characteristics, including the proportion of girls (PROP_girl) and school size (SCHSIZE). Taken together, these variables aim at capturing if school's efficiency (the ability to maximize students' achievement given the available resources) is influenced or not by a set of school's characteristics. The second group of determinants is called school's resources, including proportion of fully certified teacher (PROATCE), the index of educational material shortage (EDUSHORT), and the index of educational staff shortage (STAFFSHORT). While the efficiency model takes the *quantity* of human and material resources into account, these three variables aim at identifying the influence of the *quality* of the resources on school's efficiency. ICT infrastructure (COMPRATIO and WEBCOMP) is also included to investigate the influence of these variables on school's efficiency. The descriptive statistics of the determinants of efficiency is shown in Table 4.

In the two-stage estimation, it requires a strong assumption: the second stage determinants of efficiency (or called *environmental variables*) cannot affect the support of input and output variables in the first stage (Simar and Wilson 2007). This assumption is called the "separability condition". The second-stage regression can only be meaningful if the separability condition holds. We test this assumption using the "FEAR" package of R (Wilson 2008). The test extends the new central limit theorem results for unconditional efficiency estimators developed by Kneip et al. (2015) to conditional efficiency estimators.

To reduce computational burden, we exploit multicollinearity among the input and output variables by aggregating those inputs and outputs into a single measure (Daraio et al. 2018). Due to high degrees of correlation among the original inputs and outputs, little information is lost by this aggregation, while dimensionality is reduced from (4 + 3) = 7 to only 2. We then test the separability condition using with bandwidths optimized by least-squares cross-validation and then adjusted to obtain the optimal order (see Daraio et al. 2018 for the technical issues). The null hypothesis is that the separability condition holds. Results for the test are shown in Table 5. As we might observe, there is no evidence against separability of SCHSIZE, PROATCE, EDUSHORT, STAFFSHORT, COMPRATIO, and WEBCOMP as their p-values are more than 5%, while PROP_GIRL has p-value more than 1%. (We cannot reject the

Table 5 *p*-value for test of separability

Determinants of efficiency	*p*-value
PROP_GIRL	0.039
SCHSIZE	0.187
PROATCE	0.409
EDUSHORT	0.092
STAFFSHORT	0.886
COMPRATIO	0.436
WEBCOMP	0.478

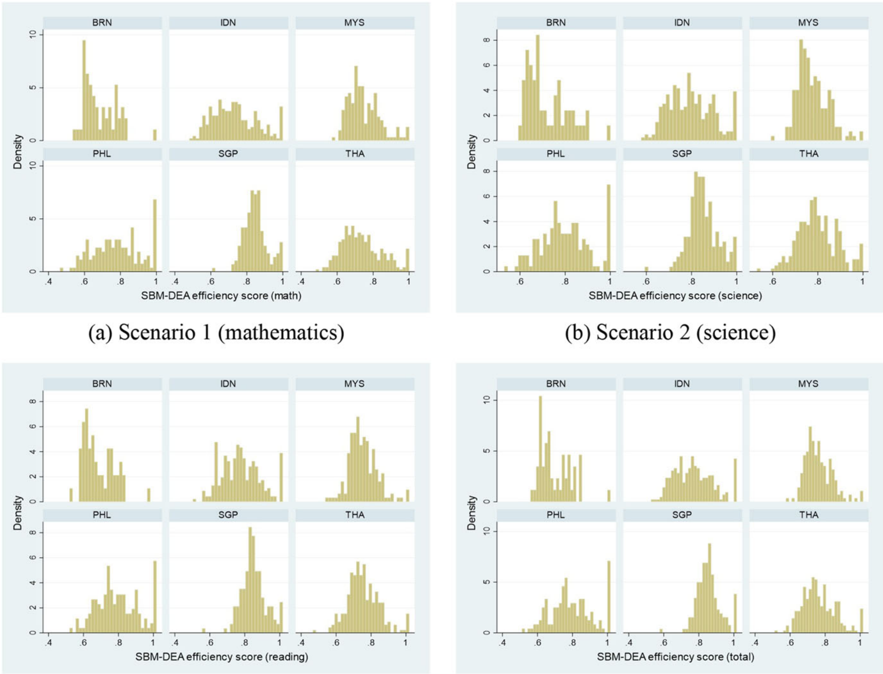
null hypothesis.) Note that we use 100 as the number of replications for jackknife bias estimates and 1000 as the number of bootstrap replications.

5 Results

Four scenarios are generated in this study, each with different outputs and identical inputs. The output of the first scenario is PVMATH, or the PISA score of mathematics, while the outputs of the second and the third scenarios are the PISA score of science (PVSCIE) and reading (PVREAD), respectively. Lastly, in the fourth scenario, all PISA domains are used as outputs. Doing this way, it is attempted to observe different behaviors that might take place.

5.1 Result of the first stage

The distributions of the efficiency score in all scenarios are shown in Fig. 1. One might notice that visually, the *patterns* are different for each country. Some countries have skewed distributions. The data that skews to the right is usually a result of a lower boundary in a data set; in this case, it is an indication of low efficiency (for example, Brunei Darussalam has the lowest average efficiency score, i.e., 0.686, 0.721, 0.686, and 0.701 in respect to the PISA score of mathematics, science, reading, and all domains, respectively). On the other hand, Singapore has the highest average value of the efficiency score in all scenarios. Interestingly, despite of the low PISA score, the Philippines is at the second place after Singapore in all scenarios. However, its standard deviation is the highest among others, implying a higher degree of heterogeneity of school's efficiency in this country. In other hand, Singapore has the lowest standard deviation, representing the information that this country might maintain *uniform* education system across its schools. This figure also highlights the presence of two different conditions in the two most efficient countries. Individually, schools in the Philippines have the lowest efficiency scores in terms of mathematics and science among other schools in the sample, while in terms of reading and all literacies, schools in Thailand have the lowest scores. The descriptive statistics is shown in Table 6. Notice that every country has the most efficient score representing by the efficiency score of



(a) Scenario 1 (mathematics)

(b) Scenario 2 (science)

(c) Scenario 3 (reading)

(d) Scenario 4 (total)

Fig. 1 The distribution of efficiency scores, by country

1 unless Brunei Darussalam (the most efficient school in this country in terms of the PISA score of reading only has efficiency score of 0.982).

In subsequent analysis, we differentiate the most efficient schools by SBM of super-efficiency model (SSBM) of Tone (2002).[3] In terms of mathematics, there are 47 efficient schools, while in science, reading, and all domains, there are 45, 50, and 59 efficient schools, respectively—later, these schools are regarded as the *super-efficient* schools. The descriptive statistics of the super-efficient schools is shown in Table 7. Even though this class of school is considered as the *best performers* among others, the discrepancy in terms of PISA score (all domains) is still high, which is reflected in the standard deviation. The super-efficient schools suffer from the low point of ESCS: the average values of ESCS in all scenarios are below the average values of ESCS in the OECD countries. The condition of ICT infrastructure at the super-efficient schools is also not quite promising since there are still many schools having low value of both ratios: COMPRATIO and WEBCOMP.

[3] The SBM-DEA model cannot discriminate inefficient DMUs as they will get the same efficiency score of 1.

Table 6 Descriptive statistics of the efficiency scores

Country	Average				Standard Deviation			
	Math	Science	Reading	Total	Math	Science	Reading	Total
BRN	0.686	0.721	0.686	0.701	0.092	0.091	0.089	0.090
IDN	0.733	0.798	0.777	0.770	0.123	0.098	0.109	0.100
MYS	0.747	0.777	0.752	0.761	0.086	0.068	0.079	0.075
PHL	0.781	0.800	0.795	0.794	0.133	0.110	0.118	0.119
SGP	0.848	0.852	0.851	0.855	0.065	0.066	0.070	0.066
THA	0.736	0.799	0.754	0.764	0.110	0.087	0.090	0.095
All	0.758	0.799	0.777	0.780	0.115	0.092	0.103	0.102
Country	**Min**				**Max**			
	Math	Science	Reading	Total	Math	Science	Reading	Total
BRN	0.544	0.597	0.538	0.562	1	1	0.982	1
IDN	0.487	0.589	0.512	0.538	1	1	1	1
MYS	0.579	0.604	0.553	0.580	1	1	1	1
PHL	0.463	0.530	0.529	0.522	1	1	1	1
SGP	0.607	0.594	0.564	0.591	1	1	1	1
THA	0.485	0.533	0.467	0.511	1	1	1	1
All	0.463	0.530	0.467	0.511	1	1	1	1

5.2 The result of the second stage

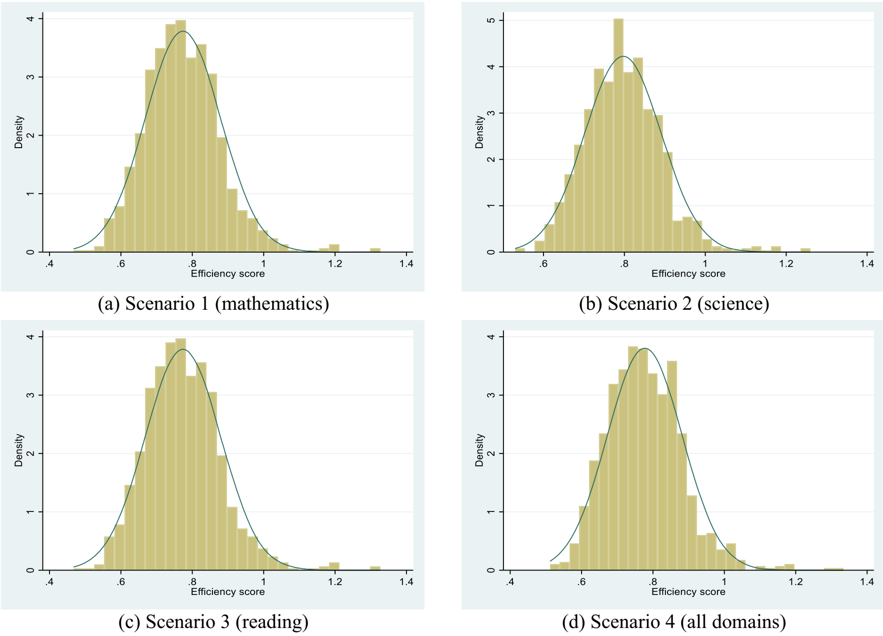
In the second stage, the influence of the determinants of efficiency is examined. The dependent variable is the efficiency score while the independent variables are the determinants of efficiency. The bootstrapped quantile regression is used for investigating the influence of the determinants of efficiency due to the benefits compared to the traditional OLS. Figure 2 shows the distribution of the efficiency score, and it indicates the skewed distributions.

The estimation result is shown in Table 8 with five quantile results of $Q_{0.1}$, $Q_{0.25}$, $Q_{0.5}$, $Q_{0.75}$, and $Q_{0.9}$. The number of bootstrap replications is set to 500. PROP_GIRL is significant (at least at the level of 10%) with positive value in all quantiles but not in the upper quantile ($Q_{0.9}$). In $Q_{0.9}$, this variable is only significant at the third scenario. It seems that among the super-efficient schools, proportion of female students does not influence their efficiency. On the other hand, this variable does matter for the low and middle efficient schools (this variable is significant in $Q_{0.1}$, $Q_{0.25}$, $Q_{0.5}$, and $Q_{0.75}$ in all scenarios).

The number of students is statistically significant with very small value in all scenarios and all quantiles. It indicates that even though the influence is significant, the effect is negligible due to the very small value. EDUSHORT negatively influences school's efficiency in all scenarios and all quantiles, while STAFFSHORT is not significant

Table 7 Descriptive statistics of the super-efficient schools

Variables	Average	Median	Standard Deviation	Min	Max
Panel A – Scenario 1 (Mathematics)					
Efficiency score	1.093	1.043	0.110	1.005	1.442
PV1MATH	500.302	459.001	125.149	345.119	687.987
PV1SCIE	491.194	443.240	113.978	350.631	676.031
PV1READ	475.568	430.334	125.358	311.676	688.732
INVSTRATIO	0.068	0.057	0.038	0.030	0.151
COMPRATIO	0.277	0.190	0.320	0.016	1.239
WEBCOMP	0.611	0.683	0.409	0.018	1.000
ESCS	−0.682	−0.853	1.305	−2.718	0.909
Panel B – Scenario 2 (Science)					
Efficiency score	1.092	1.089	0.079	1.002	1.260
PV1MATH	495.269	459.001	119.201	345.119	682.387
PV1SCIE	499.661	471.147	110.508	350.631	681.954
PV1READ	479.940	448.951	124.569	311.676	690.755
INVSTRATIO	0.068	0.058	0.037	0.030	0.151
COMPRATIO	0.300	0.201	0.347	0.016	1.380
WEBCOMP	0.621	0.683	0.399	0.018	1.000
ESCS	−0.812	−1.119	1.378	- 2.718	0.921
Panel C – Scenario 3 (Reading)					
Efficiency score	1.089	1.045	0.097	1.000	1.327
PV1MATH	485.713	439.269	117.657	345.119	685.256
PV1SCIE	484.790	441.104	107.844	350.631	681.954
PV1READ	475.198	431.599	122.450	311.676	690.755
INVSTRATIO	0.070	0.053	0.042	0.030	0.208
COMPRATIO	0.375	0.221	0.411	0.016	1.380
WEBCOMP	0.598	0.595	0.419	0.018	1.000
ESCS	−0.955	−1.120	1.343	−2.817	0.921
Panel D – Scenario 4 (All domains)					
Efficiency score	1.064	1.026	0.086	1.000	1.334
PV1MATH	504.979	461.857	121.050	345.119	687.987
PV1SCIE	499.794	444.117	112.100	350.631	681.954
PV1READ	487.446	449.203	122.905	311.676	690.755
INVSTRATIO	0.073	0.067	0.040	0.030	0.208
COMPRATIO	0.407	0.227	0.425	0.016	1.380
WEBCOMP	0.646	0.850	0.398	0.018	1.000
ESCS	−0.801	−0.956	1.337	−2.817	0.921



(a) Scenario 1 (mathematics)

(b) Scenario 2 (science)

(c) Scenario 3 (reading)

(d) Scenario 4 (all domains)

Fig. 2 The distribution of efficiency scores

in the lower and middle quantiles, but it is found significant in the upper quantile with positive value. Similar condition to STAFFSHORT is found in PROATCE. It seems that the *quality* of human resources (i.e., teacher and educational staff) plays an important role in determining efficiency at super-efficient schools.

Regarding the ICT infrastructure, COMPRATIO and WEBCOMP behave differently. The ratio of computers to the total number of students is not statistically significant in all quantiles but is significant in $Q_{0.25}$ with positive value. It is an interesting finding since the low, middle, and highly efficient schools behave similarly, but the lower-middle efficient schools see this ratio as a significant factor that influence school's efficiency. On the other hand, ratio of computers connected to the internet is found to be significant in all scenarios and all quantiles.

All countries in South-East Asia have introduced initiatives to integrate ICT in education. However, the analyzed countries are very diverse in terms of socio-economic and educational factors and they are at very different stages in their ICT integration process. Based on these different stages, Southeast Asian Ministers of Education (SEAMEO) has, in its 2010 report, broadly categorized these countries into four groups: emerging (including Cambodia, Laos, Myanmar, and East Timor), applying (none), infusing (Indonesia, the Philippines, Thailand, and Vietnam), and transforming (Brunei Darussalam, Malaysia, and Singapore) (SEAMEO 2010). It must be noted that differences exist among the countries within each group as well. Given the duration of time since the 2010 report and as new and increased efforts have been undertaken by the respective governments, it is possible that the position of the countries may have

Table 8 Parameters estimation of the bootstrapped quantile regression

Variables	$Q_{0.1}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.9}$
Panel A – Scenario 1 (Mathematics)					
Constant	0.676** (0.032)	0.702** (0.026)	0.790** (0.023)	0.886** (0.030)	1.020** (0.057)
PROP_GIRL	0.108** (0.035)	0.117** (0.027)	0.110** (0.030)	0.069* (0.039)	0.018 (0.046)
SCHSIZE	0.00002** (0.000005)	0.00002** (0.000004)	0.00002** (0.000004)	0.00003** (0.000001)	0.00003** (0.000001)
PROATCE	0.012 (0.017)	0.018 (0.014)	−0.019 (0.014)	−0.024 (0.016)	−0.050* (0.025)
EDUSHORT	−0.020** (0.004)	−0.024** (0.005)	−0.037** (0.005)	−0.035** (0.005)	−0.032** (0.006)
STAFFSHORT	0.001 (0.005)	0.003 (0.004)	0.004 (0.006)	0.008* (0.005)	0.014** (0.006)
COMPRATIO	0.008 (0.012)	0.016** (0.006)	0.009 (0.009)	−0.0001 (0.006)	−0.008 (0.009)
WEBCOMP	−0.150** (0.023)	−0.139** (0.018)	−0.124** (0.015)	−0.129** (0.023)	−0.139** (0.046)
Panel B – Scenario 2 (Science)					
Constant	0.709** (0.027)	0.736** (0.022)	0.793** (0.025)	0.884** (0.032)	1.004** (0.054)
PROP_GIRL	0.087** (0.030)	0.119** (0.022)	0.131** (0.033)	0.083** (0.037)	0.048 (0.035)
SCHSIZE	0.00001** (0.000002)	0.000011** (0.000002)	0.000013** (0.00003)	0.000013** (0.000004)	0.000014** (0.000004)
PROATCE	0.016 (0.015)	−0.003 (0.013)	−0.009 (0.012)	−0.015 (0.015)	−0.042** (0.019)
EDUSHORT	−0.015** (0.004)	−0.014** (0.004)	−0.018** (0.004)	−0.024** (0.005)	−0.023** (0.005)
STAFFSHORT	0.005 (0.005)	0.001 (0.004)	0.005 (0.004)	0.011** (0.005)	0.010** (0.005)
COMPRATIO	0.009 (0.013)	0.011** (0.005)	0.005 (0.005)	−0.008 (0.010)	−0.007 (0.010)
WEBCOMP	−0.099** (0.018)	−0.081** (0.012)	−0.082** (0.018)	−0.081** (0.022)	−0.109** (0.046)
Panel C – Scenario 3 (Reading)					
Constant	0.648 (0.031)	0.682** (0.028)	0.793** (0.025)	0.873** (0.027)	1.031** (0.050)
PROP_GIRL	0.189** (0.049)	0.162** (0.032)	0.140** (0.024)	0.103** (0.035)	0.100** (0.032)
SCHSIZE	0.000015** (0.000003)	0.000013** (0.000003)	0.000014** (0.000003)	0.000016** (0.000004)	0.000013** (0.000006)

Table 8 (continued)

Variables	$Q_{0.1}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.9}$
PROATCE	0.0001 (0.014)	0.012 (0.014)	−0.017 (0.015)	−0.022 (0.015)	−0.064** (0.028)
EDUSHORT	−0.013 (0.004)	−0.013** (0.005)	−0.021** (0.004)	−0.025** (0.005)	−0.030** (0.005)
STAFFSHORT	−0.002 (0.006)	0.001 (0.005)	0.001 (0.005)	0.006 (0.005)	0.010** (0.005)
COMPRATIO	0.003 (0.012)	0.013* (0.007)	0.006 (0.007)	−0.007 (0.006)	−0.010 (0.009)
WEBCOMP	−0.108 (0.016)	−0.097** (0.021)	−0.113** (0.017)	−0.099** (0.018)	−0.163** (0.041)
Panel D – Scenario 4 (All domains)					
Constant	0.694** (0.027)	0.710** (0.023)	0.793** (0.023)	0.866** (0.031)	1.026** (0.054)
PROP_GIRL	0.125** (0.038)	0.128** (0.025)	0.128** (0.032)	0.101** (0.030)	0.053 (0.035)
SCHSIZE	0.000017** (0.000003)	0.000015** (0.000003)	0.000017** (0.000003)	0.000018** (0.000004)	0.000018** (0.000006)
PROATCE	0.008 (0.014)	0.011 (0.015)	−0.016 (0.013)	−0.013 (0.016)	−0.058** (0.025)
EDUSHORT	−0.016** (0.004)	−0.016** (0.004)	−0.025** (0.004)	−0.029** (0.005)	−0.031** (0.005)
STAFFSHORT	0.002 (0.005)	0.001 (0.005)	0.004 (0.004)	0.011* (0.006)	0.012** (0.005)
COMPRATIO	0.006 (0.011)	0.013** (0.006)	0.012 (0.008)	−0.003 (0.006)	−0.009 (0.008)
WEBCOMP	−0.133** (0.017)	−0.105** (0.013)	−0.111** (0.016)	−0.099** (0.024)	−0.141** (0.044)

Numbers in parentheses denote the bootstrapped standard error
*significant at the level of 10%
**significant at the level of 5%

shifted along the 4-stage framework, albeit that such changes are likely to be minimal. Indeed, an up-to-date analysis of the status of ICT integration in education is required.

To distinguish if the conditional distribution of efficiency is quantile dependent, the inter-quantile tests based on the pair t-test is employed. The variance–covariance matrixes of the corresponding parameters are estimated from the bootstrap procedure with 500 replications. Table 9 shows tests of all quantile pairs for each determinant of efficiency only for Scenario 4. The null hypothesis about the equality of coefficients for different quantiles of school size is rejected. It means that the effect of school size is statistically similar in all schools, regardless of their efficiency condition. The other determinants behave differently depending on their quantiles. For example, the effect of WEBCOMP equals in all pairs but does not in the lower quantiles (i.e., $Q_{0.1}$ vs $Q_{0.25}$) even though the estimated coefficients look very similar in these two

Table 9 Results of pair t-tests for inter-quantile parameter differences in Scenario 4 (all domains)

Variables	$Q_{0.1}$ vs $Q_{0.9}$	$Q_{0.25}$ vs $Q_{0.9}$	$Q_{0.50}$ vs $Q_{0.9}$	$Q_{0.75}$ vs $Q_{0.9}$	$Q_{0.1}$ vs $Q_{0.75}$
Constant	5.88**	5.96**	4.50**	3.57**	4.95**
PROP_GIRL	−1.54	−2.04**	−1.95*	−1.67*	−0.54
SCHSIZE	0.20	0.44	0.20	−0.03	0.34
PROATCE	−2.53**	−2.69**	−1.74*	−2.15**	−1.16
EDUSHORT	−2.53**	−2.38**	−1.02	−0.32	−2.25**
STAFFSHORT	1.66*	1.80*	1.46	0.28	1.40
COMPRATIO	−1.13	−2.09**	−2.12**	−0.86	−0.76
WEBCOMP	−0.17	−0.84	−0.70	−1.14	1.36

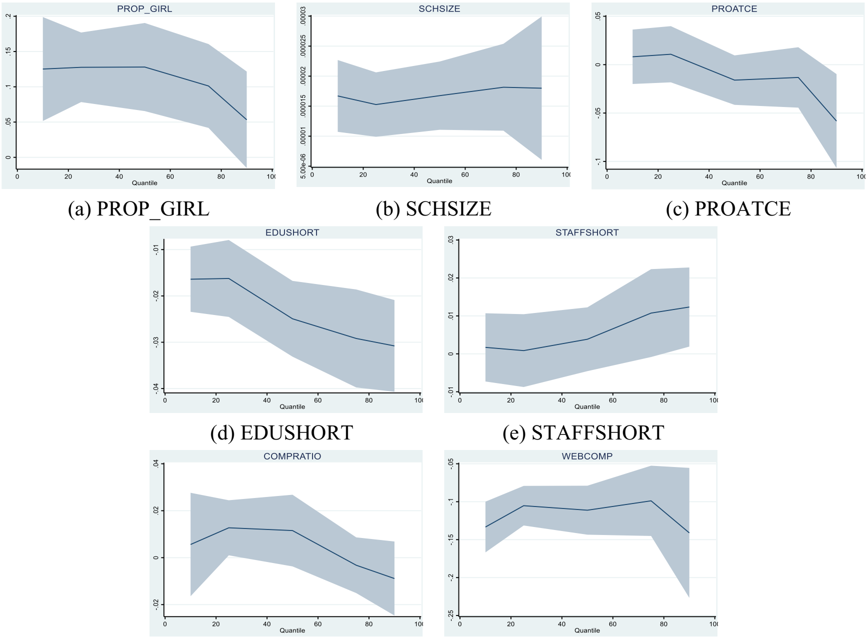
Variables	$Q_{0.25}$ vs $Q_{0.75}$	$Q_{0.50}$ vs $Q_{0.75}$	$Q_{0.1}$ vs $Q_{0.5}$	$Q_{0.25}$ vs $Q_{0.5}$	$Q_{0.1}$ vs $Q_{0.25}$
Constant	4.83**	3.05**	3.76**	3.68**	0.71
PROP_GIRL	−0.79	−0.93	0.07	0.01	0.08
SCHSIZE	0.74	0.45	0.01	0.52	−0.54
PROATCE	−1.43	0.21	−1.57	−1.88*	0.20
EDUSHORT	−2.25**	−0.92	−1.87*	−2.12**	0.04
STAFFSHORT	1.58	1.38	0.42	0.73	−0.20
COMPRATIO	−2.08**	−2.09**	0.49	−0.18	0.67
WEBCOMP	0.26	0.65	1.13	−0.41	1.92*

The numbers denote the t-value
*significant at the level of 10%
**significant at the level of 5%

quantiles. If one observes further, in this pair, all the effects of the determinants but WEBCOMP statistically equal, meaning that only the ratio of computers connected to the internet differs schools in these quantiles. It is of interest to see that the effect of this determinant statistically equals in all other pairs.

To visually represent the change in the estimated coefficients, Fig. 3 shows a visual appreciation of the bootstrapped quantile regression results only for the fourth scenario. The blue line denotes the bootstrapped quantile regression estimates, while the grey interval is the 95% confidence interval. According to Baum (2013), the graph illustrates how the effects of each determinant vary over quantiles. One can view that the influence of PROP_GIRL decreases as the quantile increases. The *stable* effect is found in the school size while the *increasing* effect is found in the index of educational staff shortage.

The final analysis is to give further evidence of the heterogeneity across countries. Table 10 reports parameters estimation in smaller samples (i.e., by country) only for Scenario 4 and in particular the upper quantile $Q_{0.9}$ (to show how the most-efficient schools behave in each country). Note that the issue of a small sample can be easily handled by using the bootstrap procedure (Simar and Wilson 2007). Looking at the



(a) PROP_GIRL (b) SCHSIZE (c) PROATCE

(d) EDUSHORT (e) STAFFSHORT

(f) COMPRATIO (g) WEBCOMP

Fig. 3 The influence of determinants of efficiency in Scenario 4 (all domains)

statistics, some similarities and differences emerge. The proportion of female students have no influence to affect the most-efficient schools in all countries. School size only has influence on school's efficiency in Indonesia and Singapore with very small magnitude. The proportion of certified teachers is significant with positive value in the super-efficient schools in the Philippines but with negative value in Indonesia and Malaysia. In terms of ICT infrastructure, the ratio of computers to the total number of students is found to be statistically significant only in Indonesia. Next, the ratio of the computers connected to the internet is statistically significant in three countries, i.e., Indonesia, Malaysia, and the Philippines.

Form the results obtained in terms of determinants of efficiency, ICT infrastructure (both ratio of computers to the total number of students and computers connected to the internet) is statistically significant only in Indonesia. Indonesia is the biggest archipelago country in South-East Asia and its major issue in education is the inequity of educational access, especially in the remote and border area. Recently, education in Indonesia emphasizes the global trending twenty-first century, which is integrating all educational activities with the use of the internet. It is shown by the National Examination which was conducted through the computer-based test in 2014. However, the equity of facilities distribution is becoming an obstacle for the government to conduct learning through the internet. Based on the survey data about Indonesian schools' condition, there are about 90.000 schools (out of 208.000 schools) which do not have access to the internet (Retnawati 2019). Surprisingly, there are 17.000

Table 10 Parameters estimation of the bootstrapped quantile regression for Scenario 4 and $Q_{0.9}$, by country

Variables	BRN ($N = 53$)	IDN ($N = 238$)	MYS ($N = 172$)	PHL ($N = 135$)	SGP ($N = 157$)	THA ($N = 252$)
Constant	0.718	1.187**	1.246**	0.631**	0.972**	0.875**
PROP_GIRL	0.221	0.030	0.058	0.249	0.073	0.071
SCHSIZE	0.00007	0.00009**	0.00002	0.00001	0.0001**	0.0000009
PROATCE	−0.044	−0.087**	−0.267**	0.217**	−0.048	0.055
EDUSHORT	−0.0096	−0.014	−0.033	−0.015	−0.0002	−−0.036**
STAFFSHORT	−0.127	0.005	−0.043*	0.020	0.006	0.036**
COMPRATIO	0.027	−0.109**	−0.015	−0.0396	−0.026	−0.003
WEBCOMP	−0.089	−0.307**	−0.180**	−0.085*	−0.157	−0.100

*significant at the level of 10%
**significant at the level of 5%

schools still experience a lack of electricity, especially in remote and border areas. This infrastructure issue that creates inequality in education makes the implementation of ICT in education a bit hampered.

Opposite results can be found in Singapore and in Thailand. As one of the modern countries today, Singapore has an outstanding development and improvement in its educational system. This successful path is supported by the intention of The Ministry of Education of Singapore to integrate ICT as the part of its education system. In 2017, ICT Development Index data showed outstanding progress for Singapore that became the country with the highest rank in ASEAN and with the 18th position in the world classification. This achievement was supported by the Technology Master Plan which was arranged by the Singaporean government to pursue a systematic and systemic approach to promote the ICT for learning into schools and continuing support for its effective adoption and deployment for teaching and learning process (Machmud et al. 2021). The Singapore Technology master plan consisted of fourth stages where the first stage was initiated in 1997. In 2012, all schools in Singapore had utilized some form of computer assisted instruction (CAI) (UIS, 2015). This *long tradition* in incorporating ICT into the education system somehow makes ICT not a "luxurious" stuff in a school since ICT are now standardized in the Singaporean schools. Therefore, it is not surprising if ICT is not a driver for the educational efficiency.

Thailand government had also shown their initiative to focus on implementing ICT in education as it started the first phase of ICT for Education Master Plan in 2000. The Ministry of Education allocated funds to provide hardware, software, and digital contents for every school under the national Thai Kem Kang project. Between 2011 and 2014, the one tablet per child (OTPC) policy was introduced which addressed *prathom* 1 for children in the primary school, grade 1 (Forhad 2018). Following the OTPC, there are several projects that the Thai government has promoted during the same period such as Thai Teachers TV, Model ICT schools and Lab schools, and Education Provision Project for Disadvantaged Children in the Highlands and Marginal Areas (Machmud et al 2021). According to the data from the UNESCO Institute of Statistics (UIS), the proportion of schools with computer assisted instruction in Thailand in 2012 was 98% (UIS, 2015), while all schools in Brunei Darussalam had utilized some form of CAI. This, in fact, also makes schools in these two countries might not consider ICT as a determinant for schools' efficiency.

6 Discussion and concluding remarks

This study analyzes the efficiency of schools in six South-East Asia countries participated in the recent OECD PISA 2018 using two-stage super-efficiency model. In the first stage, the efficiency is estimated using the SBM-DEA model while to differentiate among the efficient schools, the SBM of super-efficiency model is used. In the second stage, the bootstrapped quantile regression is applied to investigate the influence of determinants of efficiency. To date, this might be the first attempt of such an efficiency analysis in education that employs two-stage super-efficiency model using the bootstrapped quantile regression in the second stage.

To observe different behaviors that might take place, four scenarios are generated. The first scenario uses the PISA score of mathematics as output, while the second, third, and fourth scenario use the PISA score of science, reading, and all domains respectively. The inputs are set the same for all scenarios, i.e., the (inverse) of student–teacher ratio, the index of school's economics, social, and cultural status, the ratio of computers to the total number of students, and the ratio of computers connected to the internet. Singapore is widely recognized as one of the "high-performing education systems" (HPES)—a term used to describe education systems that excelled in PISA's league tables in the most recent years (Lee et al., 2014)—and has become the object of envy and emulation in many countries (see e.g., Barber and Mourshed 2007; Darling-Hammond 2010). At the top of the class on many of the international comparative measures on academic achievement, Singaporean students have surpassed many of their counterparts in traditional educational centers in North America and Europe and even Japan which was the first Asian country to modernize its education system.[4]

Factors that might influence school's efficiency are examined in the second stage by the aid of bootstrapped quantile regression using quantiles of 10%, 25%, 50% (median), 75%, and 90%. Seven determinants are included, i.e., the proportion of girls in a school, school size, proportion of fully certified teachers, index of educational material and staff shortage, the ratio of computer to the number of students, and the ratio of computers connected to the internet. Notice that among those determinants, only school size behaves similarly in all quantiles and all scenarios (i.e., positively influences efficiency with very small value). In Scenario 3, the proportion of female students at school significantly influences efficiency in all quantiles, while the ratio of computers connected to the internet does not affect school's efficiency in all quantiles. Other determinants behave differently depending on the quantiles, indicating that the conditional distribution of efficiency is quantile dependent.

The results presented here suggest several policy implications for Southern-Eastern Asian schools, indicating different courses of actions for schools with higher and lower efficiency levels. Lower efficiency schools clearly benefit more from the number of female students than higher efficiency schools. This conforms the finding of Agasisti and Zoido (2019) who found that this determinant was positively correlated with the school's efficiency in developing countries; and finding of Santín and Sicilia (2018) who found that this variable was not statistically significant to influence efficiency of schools in Spain, a developed country. The proportion of certified teachers, on the other hand, belongs to the factor that does not affect lower efficiency schools but affects the higher efficiency schools. Similar conditions also happen in the index of educational staff shortage, meaning that the quality of human resources plays an important role in determining efficiency at higher efficiency schools. High-quality school leadership includes a focus on changing or developing current classroom practices, motivating teachers, and efficient administrative support (Marzano et al. 2005).

This study also provides a shred of evidence in which heterogeneity exists across countries (see Table 10). Some differences that take places could reflect factors that are beyond the managerial efficiency of schools and could be related to welfare regimes

[4] It is encouraged to view Deng and Gopinathan (2016) who offered an explanation for the education success of Singapore.

or other institutional factors that vary across countries in South-East Asia which have different traditions and settings. This finding can be a basis for the future studies which consider more explicitly the role of supranational elements that might shape the educational provision and school's productivity (Agasisti and Zoido 2019).

As also for the future research, a network DEA can be considered. In this study, the (educational) production technology is treated as a black box that transforms inputs into outputs. However, in most real situations, the DMUs may perform several different functions and can also be separated into different components either in series or in parallel and/or in a more complex form of network type. In such situations, some components play important roles in producing outputs through the use of intermediate outputs obtained from their previous components. The network DEA then accounts for divisional efficiencies as well as the overall efficiency in a unified framework (see, e.g., Cook et al. 2010; Färe and Grosskopf 1996; Lindsay 1982). The network DEA has been applied in several sectors, such as in healthcare (e.g., Ferreira et al. 2021; Pereira et al. 2022) and airlines (e.g., Soltanzadeh and Omrani 2018; Yu and See 2023). In the education, this model has been applied most in the context of higher education (e.g., Lee and Johnes, 2022; Monfared and Safi 2013; Tavares et al. 2021). The rationale lies that research can be considered as "output" from teaching activities and a network model can be drawn from this perspective. However, in the context of high school and the used of PISA data, as in this research, that rationale is hard to be justified. Nevertheless, we might consider this model in the future research in the regards to the availability of the relevant data.

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References

Agasisti, T.: The efficiency of public spending on education: an empirical comparison of EU countries. Eur. J. Educ. **49**(4), 543–557 (2014)

Agasisti, T., Zoido, P.: The efficiency of schools in developing countries, analysed through PISA 2012 data. Socioecon. Plann. Sci. **68**, 100711 (2019)

Agasisti, T., Munda, G., Hippe, R.: Measuring the efficiency of European education systems by combining data envelopment analysis and multiple-criteria evaluation. J. Prod. Anal. **51**(2–3), 105–124 (2019)

Agha, S.R., Kuhail, I., Abdul Nabi, N., Salem, M., Ghanim, A.: Assessment of academic departments efficiency using data envelopment analysis. J. Ind. Eng. Manag. **4**(2), 301–325 (2011)
Amaral, C., Pedro, M.I., Ferreira, D.C., Marques, R.C.: Performance and its determinants in the Portuguese municipal solid waste utilities. Waste Manage. **139**, 70–84 (2022)
Andersen, P., Petersen, N.C.: A procedure for ranking efficient units in data envelopment analysis. Manage. Sci. **39**(10), 1261–1264 (1993)
Angrist, J., Chernozhukov, V., Fernández-Val, I.: Quantile regression under misspecification, with an application to the US wage structure. Econometrica **74**(2), 539–563 (2006)
Aristovnik, A.: ICT expenditures and education outputs/outcomes in selected developed countries: an assessment of relative efficiency. Campus-Wide Inf. Syst. **30**(3), 222–230 (2013)
Arshad, M., Amjath-Babu, T.S., Aravindakshan, S., Krupnik, T.J., Toussaint, V., Kächele, H., Müller, K.: Climatic variability and thermal stress in Pakistan's rice and wheat systems: A stochastic frontier and quantile regression analysis of economic efficiency. Ecol. Ind. **89**, 496–506 (2018)
Asian Development Bank: Asian development outlook 2011. Asian Development Bank, Manila (2011)
Avvisati, F.: The measure of socio-economic status in PISA: a review and some suggested improvements. Large-Scale Assess Educ (2020). https://doi.org/10.1186/s40536-020-00086-x
Banker, R.D., Charnes, A., Cooper, W.W.: Models for the estimation of technical and scale inefficiencies in data envelopment analysis. Manage. Sci. **30**, 1078–1092 (1984)
Barber, M., Mourshed, M.: How the world's best-performing school systems come out on top. McKinsey & Company, London (2007)
Baum CF (2013) Quantile regression. http://fmwww.bc.edu/EC-C/S2016/8823/ECON8823.S2016.nn04.slides.pdf
Castano, M.C.N., Cabanda, E.C.: Performance evaluation of the efficiency of Philippine private higher educational Institutions: application of frontier approaches. Int. Trans. Oper. Res. **14**(5), 431–444 (2007)
Charnes, A., Cooper, W.W., Rhodes, E.: Measuring the efficiency of decision making units. Eur. J. Oper. Res. **2**(6), 429–444 (1978)
Charnes, A., Cooper, W.W., Golany, B., Seiford, L.M., Stutz, J.: Foundation of data envelopment analysis and Pareto-Koopmans empirical production functions. J. Econom **30**, 91–107 (1985)
Chen, X., Shu, X.: The scientific and technological innovation performance of Chinese world-class universities and its influencing factors. IEEE Access **9**, 84639–84650 (2021)
Cheng, Y.C.: Recent education developments in South East Asia: an introduction. Sch. Eff. Sch. Improv. **10**(1), 3–9 (1999)
Comi, S.L., Argentin, G., Gui, M., Origo, F., Pagani, L.: Is it the way they use it? Teachers, ICT and student achievement. Econ. Educ. Rev. **56**, 24–39 (2017)
Cook, W.D., Liang, L., Zhu, J.: Measuring performance of two-stage network structures by DEA: a review and future perspective. Omega **38**(6), 423–430 (2010)
Cooper, W.W., Seiford, L.M., Tone, K.: Introduction to data envelopment analysis and its uses: With DEA-solver software and references. Springer, Boston (2006)
Crespo-Cebada, E., Pedraja-Chaparro, F., Santín, D.: Does school ownership matter? An unbiased efficiency comparison for regions of Spain. J. Prod. Anal. **41**(1), 153–172 (2014)
Daraio, C., Simar, L., Wilson, P.W.: Central limit theorems for conditional efficiency measures and tests of the 'separability' condition in non-parametric, two-stage models of production. Economet. J. **21**(2), 170–191 (2018)
Darling-Hammond, L.: The flat world and education: How America's commitment to equity will determine our future. Teachers College Press, New York, NY (2010)
De Witte, K., Rogge, N.: Does ICT matter for effectiveness and efficiency in mathematics education? Comput. Educ. **75**, 173–184 (2014)
Deng, Z., Gopinathan, S.: PISA and high-performing education systems: explaining Singapore's education success. Comp. Educ. **52**(4), 449–472 (2016)
Efron, B., Tibshirani, R.: Bootstrap methods for standard errors, confidence intervals, and other measures of statistical accuracy. Stat. Sci. **1**(1), 54–75 (1986)
Falck, O., Mang, C., Woessmann, L.: Virtually no effect? Different uses of classroom computers and their effect on student achievement. Oxford Bull. Econ. Stat. **80**(1), 1–38 (2018)
Färe, R., Grosskopf, S.: Productivity and intermediate products: a frontier approach. Econ. Lett. **50**(1), 65–70 (1996)

Ferreira, D.C., Marques, R.C., Pedro, M.I.: Comparing efficiency of holding business model and individual management model of airports. J. Air Transp. Manag. **57**, 168–183 (2016)

Ferreira, D.C., Marques, R.C., Pedro, M.I.: Explanatory variables driving the technical efficiency of European seaports: an order-α approach dealing with imperfect knowledge. Transp Res Part e: Logist Transp Rev **119**, 41–62 (2018a)

Ferreira, D.C., Marques, R.C., Nunes, A.M.: Economies of scope in the health sector: the case of Portuguese hospitals. Eur. J. Oper. Res. **266**(2), 716–735 (2018b)

Ferreira, D.C., Graziele, I., Marques, R.C., Gonçalves, J.: Investment in drinking water and sanitation infrastructure and its impact on waterborne diseases dissemination: the Brazilian case. Sci. Total. Environ. **779**, 146279 (2021)

Ferrera, J.M.C., Cebada, E.C., Chaparro, F.P., Santín, D.: Exploring educational efficiency divergences across Spanish regions in PISA 2006. Rev De Econ Apl **19**(57), 117–145 (2011)

Forhad, Z.A.: In-service teachers' attitudes toward and usage of information communication technology (ICT) tools in professional practice; a study of an international school in Bangkok, Thailand. J. Appl. Math. Comput. **2**(4), 116–135 (2018)

Frýd, L., Sokol, O.: Relationships between technical efficiency and subsidies for Czech farms: a two-stage robust approach. Socioecon. Plann. Sci. **78**, 101059 (2021)

Fu, J.: Complexity of ICT in education: a critical literature review and its implications. Int. J. Educ. Dev. Using Inf. Commun. Technol. **9**(1), 112–125 (2013)

Gajewski, B.J., Lee, R., Bott, M., Piamjariyakul, U., Taunton, R.L.: On estimating the distribution of data envelopment analysis efficiency scores: an application to nursing homes' care planning process. J. Appl. Stat. **36**(9), 933–944 (2009)

Grimes, D., Warschauer, M.: Learning with laptops: a multi-method case study. J. Educ. Comput. Res. **38**(3), 305–332 (2008)

Gronewold, N. (2019). *Booming Southeast Asia's dirty secret: coal*. E&E News. Available from: https://subscriber.politicopro.com/article/eenews/1061593609.

Guan, W.: From the help desk: bootstrapped standard errors. Stata Journal **3**(1), 71–80 (2003)

Handayani, N. U., Sari, D. P., Ulkhaq, M. M., Widharto, Y., & Fitriani, R. C. A. A data envelopment analysis approach for assessing the efficiency of sub-sectors of creative industry: a case study of batik enterprises from Semarang, Indonesia. In AIP Conference Proceedings. Vol. 2217(1). AIP Publishing. (2020)

Ibrahim, M.D., Alola, A.A., Ferreira, D.C.: A two-stage data envelopment analysis of efficiency of social-ecological systems: inference from the sub-Saharan African countries. Ecol. Ind. **123**, 107381 (2021)

Johnes, G., Virmani, S.: The efficiency of private and public schools in urban and rural areas: moving beyond the development goals. Int. Trans. Oper. Res. **27**(4), 1869–1885 (2020)

Kneip, A., Simar, L., Wilson, P.W.: When bias kills the variance: central limit theorems for DEA and FDH efficiency scores. Economet. Theor. **31**(2), 394–422 (2015)

Koenker, R., Bassett, G., Jr.: Regression quantiles. Econometrica **46**(1), 33–50 (1978)

Kumbhakar, S.C., Lovell, C.K.: Stochastic frontier analysis. Cambridge University Press (2000)

Lavado, R.F., Cabanda, E.C.: The efficiency of health and education expenditures in the Philippines. CEJOR **17**(3), 275–291 (2009)

Le, M.H., Afsharian, M., Ahn, H.: Inverse frontier-based benchmarking for investigating the efficiency and achieving the targets in the Vietnamese education system. Omega **103**, 102427 (2021)

Le, T.D., Ngo, T., Ho, T.H., Nguyen, D.T.: ICT as a key determinant of efficiency: a bootstrap-censored quantile regression (BCQR) analysis for Vietnamese banks. Int. J. Financ. Stud. **10**(2), 44 (2022)

Lee, K.: Do charter schools spur improved efficiency in traditional public schools in Michigan? KEDI J. Educ. Policy **6**(1), 41–59 (2009)

Lee, Y.-J.: Science Education in a Straightjacket: the Interplay of People, Policies, and Place in an East Asian Developmental State. In: Tan, A.-L., Poon, C.-L., Lim, S.L. (eds.) Inquiry into the Singapore science classroom, pp. 165–189. Springer, Singapore (2014)

Lee, B.L., Johnes, J.: Using network DEA to inform policy: the case of the teaching quality of higher education in England. High. Educ. q. **76**(2), 399–421 (2022)

Lei, J., Zhao, Y.: One-to-one computing: what does it bring to schools? J. Educ. Comput. Res. **39**(2), 97–122 (2008)

Lindsay, A.W.: Institutional performance in higher education: the efficiency dimension. Rev. Educ. Res. **52**(2), 175–199 (1982)

Machmud, M.T., Widiyan, A.P., Ramadhani, N.R.: The development and policies of ICT supporting educational technology in Singapore, Thailand, Indonesia, and Myanmar. Int. J. Eval. Res. Educ. **10**(1), 78–85 (2021)

Marzano, R.J., Waters, T., McNulty, B.A.: School leadership that works: from research to results. Association for Supervision and Curriculum Development, Alexandria (2005)

Monfared, M.A.S., Safi, M.: Network DEA: an application to analysis of academic performance. J. Ind. Eng. Int. **9**, 1–10 (2013)

Moutinho, V., Madaleno, M., Robaina, M.: The economic and environmental efficiency assessment in EU cross-country: evidence from DEA and quantile regression approach. Ecol. Ind. **78**, 85–97 (2017)

Nwaogbe, O.R., Wanke, P., Ogwude, I.C., Barros, C.P., Azad, A.K.: Efficiency driver in Nigerian airports: a bootstrap DEA–censored quantile regression approach. J Aviat Technol Eng **7**(2), 2 (2018)

OECD: PISA 2018: insights and interpretations. OECD Publishing, Berlin (2019)

Pereira, M.A., Dinis, D.C., Ferreira, D.C., Figueira, J.R., Marques, R.C.: A network data envelopment analysis to estimate nations' efficiency in the fight against SARS-CoV-2. Expert Syst. Appl. **210**, 118362 (2022)

Perelman, S., Santín, D.: Measuring educational efficiency at student level with parametric stochastic distance functions: an application to Spanish PISA results. Educ. Econ. **19**(1), 29–49 (2011a)

Perelman, S., Santín, D.: Imposing monotonicity on outputs in parametric distance function estimations. Appl. Econ. **43**(30), 4651–4661 (2011b)

Pramono, S. N. W., Ulkhaq, M. M., Pujotomo, D., & Ardhini, M. A. Assessing the efficiency of small and medium industry: an application of data envelopment analysis. In: IOP Conference Series: Materials Science and Engineering. Vol. 598(1), p. 012043. IOP Publishing. (2019)

Qi, S., Peng, H., Zhang, X., Tan, X.: Is energy efficiency of belt and road Initiative countries catching up or falling behind? Evidence from a panel quantile regression approach. Appl. Energy **253**, 113581 (2019)

Retnawati, E.: Efforts to support and expand the use of educational technology as a means of delivering learning. Int. J. Indones Educ Teach **3**(1), 128–137 (2019)

Salas-Velasco, M.: Assessing the performance of Spanish secondary education institutions: distinguishing between transient and persistent inefficiency, separated from heterogeneity. Manch. Sch. **88**(4), 531–555 (2020)

Salcedo, R.E.: Performance efficiency of the teacher education programs of a state university in the Philippines: a data envelopment analysis study. J. Crit. Rev **7**(7), 96–103 (2020)

Santín, D., Sicilia, G.: Dealing with endogeneity in data envelopment analysis applications. Expert Syst. Appl. **68**, 173–184 (2017)

Santín, D., Sicilia, G.: Using DEA for measuring teachers' performance and the impact on students' outcomes: evidence for Spain. J. Prod. Anal. **49**(1), 1–15 (2018)

Sari, D. P., Handayani, N. U., Ulkhaq, M. M., Budiawan, W., Maharani, D. L., & Ardi, F. A data envelopment analysis approach for assessing the efficiency of small and medium-sized wood-furniture enterprises: a case study. In: MATEC Web of Conferences Vol. 204, p. 01015. EDP Sciences, (2018)

SEAMEO: Report: status of ICT integration in education in southeast Asian countries. SEAMEO, Bangkok (2010)

Simar, L., Wilson, P.W.: Estimation and inference in two-stage, semi-parametric models of production processes. J. Econom. **136**(1), 31–64 (2007)

Sirin, S.: Socioeconomic status and academic achievement: a meta-analytic review of research. Rev. Educ. Res. **75**(3), 417–453 (2005)

Soltanzadeh, E., Omrani, H.: Dynamic network data envelopment analysis model with fuzzy inputs and outputs: an application for Iranian Airlines. Appl. Soft Comput. **63**, 268–288 (2018)

Sowlati, T., Paradi, J.C.: Establishing the "practical frontier" in data envelopment analysis. Omega **32**(4), 261–272 (2004)

Symaco, L.P., Chao, R.Y.: Comparative and International Education in East and South East Asia. In: Wolhuter, C.C., Wiseman, A.W. (eds.) Comparative and international education: survey of an infinite field, vol. 36, pp. 213–228. Emerald Publishing Limited, Leeds (2019)

Tavares, R.S., Angulo-Meza, L., Sant'Anna, A.P.: A proposed multistage evaluation approach for higher education institutions based on network data envelopment analysis: a Brazilian experience. Eval. Program Plann. **89**, 101984 (2021)

Tone, K.: An ε-free DEA and a new measure of efficiency. J Op Res Soc Jpn **36**, 167–174 (1993)

Tone, K.: A slacks-based measure of efficiency in data envelopment analysis. Eur. J. Oper. Res. **130**(3), 498–509 (2001)
Tone, K.: A slacks-based measure of super-efficiency in data envelopment analysis. Eur. J. Oper. Res. **143**, 32–41 (2002)
Türkan, S., Özel, G.: Efficiency of state universities in Turkey during the 2014–2015 academic year and determination of factors affecting efficiency. Educ. Sci. **42**(191), 307–322 (2017)
Ulkhaq, M.M.: Assessing technical efficiency of large and medium manufacturing industry in West Java Province, Indonesia: a data envelopment analysis approach. ES Manag. Bus. **1**(01), 24–30 (2022)
Ulkhaq, M.M.: Technical efficiency of indonesian sharia banks: a data envelopment analysis approach. Al-Muhasib: J Islamic. Account. Financ. **3**(1), 86–99 (2023a)
Ulkhaq, M.M.: A slacks-based measure of efficiency in data envelopment analysis to assess efficiency of Indonesian sharia banks. Khatulistiwa **13**(1), 37–46 (2023b)
Ulkhaq, M.M.: Logistics Performance Measurement: a Data Envelopment Analysis Using the Logistics Performance Index 2018 Data. In: Data-driven technologies and artificial intelligence in supply chain, pp. 58–76. CRC Press, Boca Raton (2024)
Ulkhaq, M.M., Pratiwi, T.N.: A data envelopment analysis approach to assess technical efficiency of large and medium manufacturing industry in central java province Indonesia. Int. Econ. Financ. Rev. **1**(2), 54–65 (2022)
UNESCO Institute of Statistics (UIS, 2015). A Review of Education and ICT Indicators in Southeast Asia. Accessed from http://www.unescobkk.org/education/ict/online-resources/databases/ict-ineducation-database/item/article/areview-of-education-and-ict-indicators-insoutheast-asia-by-unesco-bangkok/
Venable, J.R., Pries-Heje, J., Bunker, D., Russo, N.L.: Design and diffusion of systems for human benefit: toward more humanistic realization of information systems in society. Inf. Technol. People **24**(3), 208–216 (2011)
Willms, J.D., Tramonte, L.: The measurement and use of socioeconomic status in educational research. In: Suter, L.E., Denman, B., Smith, E. (eds.) The SAGE handbook of comparative studies in education. Sage, London (2019)
Wilson, P.W.: FEAR 1.0: A software package for frontier efficiency analysis with R. Socioecon. Plann. Sci. **42**, 247–254 (2008)
Woetzel, J., Madgavkar, A., Seong, J., Manyika, J., Sneader, K., Tonby, O., Cadena, A., Gupta, R., Leke, A., Kim, H., Gupta, S.: Outperformers: high-growth emerging economies and the companies that propel them. McKinsey Global Institute, New York (2018)
Wohlrabe, K., de Moya Anegon, F., Bornmann, L.: How efficiently do elite US universities produce highly cited papers? Publications **7**(1), 4 (2019)
World Bank: Emerging stronger from the crisis, world bank East Asia and Pacific economic update, vol. 1. The International Bank for Reconstruction and Development/The World Bank, Washington (2010)
Yu, M.M., See, K.F.: Evaluating the efficiency of global airlines: a new weighted SBM-NDEA approach with non-uniform abatement factor. Res. Transp. Bus. Manag. **46**, 100860 (2023)
Zhang, S., Wang, X.: Does innovative city construction improve the industry–university–research knowledge flow in urban China? Technol. Forecast. Soc. Chang. **174**, 121200 (2022)
Zhang, S., Wang, X., Zhang, B.: Innovation ability of universities and the efficiency of university–industry knowledge flow: the moderating effect of provincial innovative agglomeration. Chin. Manag. Stud. **16**(2), 446–465 (2022)
Zoghbi, A.C., Rocha, F., Mattos, E.: Education production efficiency: evidence from Brazilian universities. Econ. Model. **31**, 94–103 (2013)
Zou, L., Zhu, Y.W.: Universities' scientific and technological transformation in China: its efficiency and influencing factors in the Yangtze River economic belt. PLoS ONE **16**(12), e0261343 (2021)