Efficiency Analysis of Indonesian Schools: A Stochastic Frontier Analysis using OECD PISA 2018 Data

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Abstract

The importance of high-quality education as a source of economic growth and well-being is broadly acknowledged. Enhancing the efficiency of schooling system as well as individual schools are considered as a means to improve the provision of better-quality education. With imperfect markets for the services in the education sector, it is vital to assess the efficiency. This study aims to measure the efficiency of Indonesian schools which participated in PISA 2018. Stochastic frontier analysis (SFA) was used to accomplish the objective of the study. The data were modeled into four different models by considering the distribution assumption of inefficiency, i.e., (i) half-normal model, (ii) truncated-normal model, (iii) exponential model, and (iv) heteroscedastic model. The last model is presented to consider the determinants of inefficiency. The PISA score of reading literacy was considered as a dependent variable, while seven independent variables are: index of school's economic, social and cultural status, type of school, school size, class size, student-teacher ratio, as well as student- and teacher behavior hindering learning. The ICT infrastructure was selected as determinants of inefficiency. This study is expected to give an insight about how to apply SFA in the field of education as well as how to interpret the results.

Keywords
Education, Efficiency, Indonesia, School performance, Stochastic frontier analysis.

1. Introduction
The term efficiency commonly refers to the ratio of output to input, and it is widely used as a measure of performance evaluation (Cooper et al. 2006). In the field of education, the expression is used to describe the ability of an entity (student, school, or university) to produce a given level of output(s) with the number of available input(s) (Agasisti and Gralka 2019). The outputs are commonly related to the achievements obtained by the students (Mizala et al. 2002, Portela et al. 2012, Silva et al. 2020), proportion of students accomplishing more than a certain grade (Bradley and Taylor 1998), number of graduates (Kirjavainen, and Loikkanen 1996), attendance rate (Arnold et al. 1996, Bradley and Taylor 1998), number of success rates (Kirjavainen, and Loikkanen 1996, Muñiz 2002), and proportion of students who do not drop out (Arnold et al. 1996). On the other hand, there are three kinds of variables reflecting the inputs: (i) characteristics of school, e.g., size of school, number of teachers, (ii) characteristics of teacher, e.g., level of education, salary, and (iii) characteristics of students, e.g., socio-economic characteristics, prior attainment.

Although there are extensive studies on the efficiency assessment, in education literature, the efficiency is mainly assessed by frontier methods: non-parametric, e.g., data envelopment analysis (DEA), and parametric, i.e., stochastic frontier analysis (SFA). The application of DEA was fairly common due to its flexibility and simplicity. It can handle multiple outputs and inputs more simply and it does not require any assumption about the functional form. However, as a deterministic approach, DEA assumes that all deviations from a frontier (or the most efficient one) are because of inefficiency. It means that DEA does not distinguish inefficiency from other factor, such as statistical noise, resulting that it may overestimate the level of inefficiency. Contrarily, in the SFA, the drawback can be avoided since it does differentiate the deviation as inefficiency and statistical disturbance. In addition, as a parametric approach, one can observe the effect of the inputs on the outputs. The possibility to analyze panel data to control unobserved heterogeneity further escalates SFA's attractiveness over DEA.

Despite of its benefits, research of applying SFA in education are in minority compared to DEA (Witte and Torres 2017). Some research employing SFA in the field of education that can be mentioned are as follows. Agasisti and

Gralka (2019) estimated the transient and persistent efficiency of Italian and German universities; Minaya and Agasisti (2019) evaluated the stability of school performance in Italian context; Kirjavainen (2012) assessed the efficiency of Finnish general upper secondary schools; and Agasisti and Belfield (2017) measured the efficiency in the community college sector. This study tried to measure the efficiency of Indonesian schools by applying SFA. The OECD PISA 2018 data was used to accomplish the objective of the study. As the best of my knowledge, such attempt remains limited. Therefore, this study tried to expand the application of SFA in the field of education, especially in Indonesia. This study tried to model the data into four different models according to distribution assumption of inefficiency (see Section 2 for more detail). It employed Stata, a data analysis and statistical software established by StataCorp in 1985. This is motivated by the recognition of Stata in the field of econometrics; and also, by the aid of its well-established SFA packages.

The paper is then structured as follows. The following section presents method used as well as four different models generated. The data and variables used in this study would be exhibited in Section 3. Next, results of each model and accompanying discussion are shown in Section 4. Finally, conclusion and future research direction are presented in the last section.

2. Method and Models

A production frontier specifies the maximum output that can be produced from a specified set of inputs, given the existing technology available to the firms involved. Analogously, the educational production function assumes an educational institution as an entity which transforms inputs into outputs through a production process (Worthington 2001). There are two main perspectives of analysis to view the function, i.e., value-added and value for money (Mayston 2003). While the first is related to the school effectiveness, the latter is associated to the school efficiency. Accordingly, school is believed to be effective if it is able to add more value to the students. In this context, schools are compared according to the degree which they engage their students into successful academic paths, measured through the educational outcome (Portela and Camanho 2010). In the value for money perspective, schools are viewed as entities which consume resources or input (e.g., time, money, etc.) to produce outputs (e.g., high grades in exams, number of graduates etc.). In this context, an efficient school is which that consumes the minimum inputs to attain a given quantity of outputs (Silva et al. 2020). In this research, the value-added perspective is adopted.

The stochastic frontier (educational) production function is defined as follows

$$ln\ y_i = f(\mathbf{x}_i; \boldsymbol{\beta}) + v_i - u_i, \tag{1}$$

where y_i is an observed output for an observation i, acting as a solely dependent variable; $f(\bullet)$ is the (educational) production function; $\mathbf{x}_i$ is a vector of inputs; $\boldsymbol{\beta}$ is the associated vector of parameters to be estimated; v_i is the two-sided statistical noise; and u_i is the nonnegative technical inefficiency. Notice that the inefficiency is considered as an "error term"; thus, Equation (1) can be written as $ln\ y_i = f(\mathbf{x}_i; \boldsymbol{\beta}) + \varepsilon_i$, where ε_i is the composed error ($\varepsilon_i = v_i - u_i$). There are several production functions proposed in the literature; in this study, the linear function was selected for the sake of simplicity.

Equation (1) can be estimated in two steps. In the first step, assuming that v_i and u_i are distributed independently of $\mathbf{x}_i$, the ordinary least squares procedure would provide consistent estimates of $\boldsymbol{\beta}_k$ but not β_0. The second step involves the use of maximum likelihood procedure to estimate β_0 and the variances of v_i and u_i; thus, distributional assumptions are required. Several scholars have proposed some pairs of distributional assumptions for v_i and u_i. While most agreed that $v_i \sim$ IID $N(0,\sigma_v^2)$, meaning that v_i is assumed to independent and identically distributed and follow the normal distribution with zero mean and variance $\boldsymbol{\sigma_v^2}$, the distribution of u_i differs across studies. In this study, the half-normal distribution by Aigner et al. (1977), the truncated-normal distribution by Stevenson (1980), and the exponential distribution by Meeusen and Broeck (1977) were used.

2.1 Model 1: The Half-normal Model

Considering Equation (2), the following distributional assumptions for Model 1 are presented: (i) $v_i \sim$ IID $N(0,\boldsymbol{\sigma_v^2})$; (ii) $u_i \sim$ IID $N^+(0,\boldsymbol{\sigma_u^2})$, meaning that u_i is assumed to follow half-normal distribution with zero mode and variance $\boldsymbol{\sigma_u^2}$; and (iii) v_i and u_i are distributed independently of each other, and of $\mathbf{x}_i$. See Kumbhakar and Lovell (2003) and Kumbhakar et al. (2015) who provided the extensive discussion about how to estimate the parameters. After the parameters are estimated, the inefficiency can be estimated by exploiting the conditional distribution of u_i given (v_i –

u_i). Jondrow et al. (1982)—later on it is called JLMS estimator—proposed the conditional mean as a point estimate of technical inefficiency u_i. The efficiency is estimated by using the BC estimator proposed by Battese and Coelli (1988). This model is based on the plausible proportion that the modal value of inefficiency is zero, with increasing values of inefficiency becoming increasingly less likely. It implies that there is a tendency for higher efficiency for the majority of the observations.

2.2 Model 2: The Truncated-normal Model

The one-parameter half-normal distribution is inherently restrictive; for instance, the distribution implies that most of the observations are clustered near full efficiency. However, it can be argued that some of them might exhibit a certain degree of inefficiency. Stevenson (1980) proposed a truncated-normal model which allows the inefficiency distribution to have a non-zero mode. The notation $u_i \sim$ IID $N^+(\mu,\boldsymbol{\sigma_u^2})$ indicates a truncation of the normal distribution $N(\mu,\boldsymbol{\sigma_u^2})$ at 0 (zero) from above. After the parameters are being estimated, the JLMS and BC estimator can be used to estimate the inefficiency and efficiency, respectively.

2.3 Model 3: The Exponential Model

The distributional assumptions for this model are: (i) $v_i \sim$ IID $N(0,\boldsymbol{\sigma_v^2})$; (ii) $u_i \sim$ IID $Expo(1/\lambda)$, meaning that u_i is assumed to follow exponential distribution with parameter $1/\lambda$; and (iii) v_i and u_i are distributed independently of each other, and of $\mathbf{x}_i$. See Kumbhakar and Lovell (2003) and Kumbhakar et al. (2015) for more elaboration towards how to estimate the parameters. The inefficiency and efficiency can be estimated by employing JLMS and BC estimator, respectively.

2.4 Model 4: The Heteroscedastic Model

In some cases, researchers might not only want to know the levels of inefficiency, but also the factors that can explain inefficiency, called the determinants of inefficiency. For instance, in analyzing the efficiency of the dairy industry, a researcher might want to know whether the inefficiency of a farm is affected by, say, the use of information technology, the farmer's education, or the type of ownership. The previous models, however, cannot consider this issue since inefficiency is regarded as an error. (Those models are called homoscedastic since they assumed that $\boldsymbol{\sigma_u^2}$ parameter is constant.) Caudill and Ford (1993), Caudill et al. (1995), and Hadri (1999) consider models in which the error terms are heteroscedastic. In this study, the heteroscedasticity is reflected by $\boldsymbol{\sigma_u^2}$ = exp ($\mathbf{z}_i$;$\mathbf{w}$), where $\mathbf{z}_i$ is the determinants of inefficiency and $\mathbf{w}$ is corresponding parameter vector. Notice that in this research, half-normal distribution assumption is used in Model 4.

3. Data and Variables

I took advantage of the information available in the recent OECD PISA database (i.e., PISA 2018) to accomplish the objective of the study. In PISA 2018, about six hundred thousand students were examined, representing about thirty-two million students of seventy-nine participating countries. In Indonesia, there are 12,098 students from 397 schools who participated in PISA 2018. The database can be freely downloaded in the OECD website.

The dependent variable (or the educational output) is the PISA score of reading literacy since reading is the main subject assessed in PISA 2018. Because this study is conducted in the school level, the students' scores were aggregated to obtain the weighted PISA score for each school by using the final student weight provided by PISA (variable name: W_PV_READ)[1]. In this study, there are seven independent variables, i.e., index of economic, social and cultural status (ESCS), aggregated for each school (W_ESCS), type of school (SCHTYPE), school size or number of enrolled students (SCHSIZE), class size or number of students in each class (CLSIZE), student-teacher ratio (STRATIO), student behavior hindering learning (STUBEHA), and teacher behavior hindering learning (TEACHBEHA). ESCS is estimated by using parents' education, occupation, and availability of household assets. The index is constructed to obtain a distribution with zero mean and unit standard deviation for the country. ESCS has been widely known to explain the educational output, see for example Agasisti and Zoido (2019), Crespo-Cebada et al. (2014), and Salas-Velasco (2020). There are three type of school considered in PISA, i.e., public, private independent, and private government independent. Regarding this variable, literature shows that it may importantly affect the performance of the students, see for example Cyrenne and Chan (2012), Mora and Escardibul (2008), and

[1] In PISA, student's score in each domain's literacy were stored as a "plausible value" (PV) variable. For each domain, several PVs were generated. In this study, only the first PV was used.

Smith and Naylor (2005). Size of school effect (measured by number of students or number of students per class) has been proposed as determinants of student achievement by several studies, e.g., Crespo-Cebada et al. (2014), Podinovski et al. (2014), and Kirjavainen (2012). The student-teacher ratio might affect the educational output as shown by Agasisti (2014), Agasisti and Zoido (2019), and Agasisti et al. (2019).

To make a contribution, this study includes two variables reflecting school climate (STUHBEHA and TEACHBEHA). The variables reflect the school principal's perceptions of teacher and student behavior that might influence the provision of instruction at school. Similar to ESCS, these variables were generated to obtain a distribution with zero mean and unit standard deviation for the country.

This study considers two variables to be determinants of inefficiency, i.e., ratio of computers to the total number of students (RATCMP1) and ratio of computers to the number of these computers that were connected to the Internet (RATCMP2). These variables are included since it might be interested to investigate whether inefficiency is affected by ICT infrastructure. These variables also can be "easily" adjusted/changed by the institution (school).

4. Results and Discussion

4.1 Descriptive Statistics

Eight variables were used which consist of one dependent variable (W_PV_READ), seven independent variables (W_ESCS, SCHTYPE, SCHSIZE, CLSIZE, STRATIO, STUBEHA, and TEACHBEHA), and two determinants of inefficiency (RATCMP1 and RATCMP2). Table 1 presents descriptive statistics for the numerical variables used in this study. Notice that qualitative variable, i.e., SCHTYPE, was excluded; also, missing values of each variable were removed from the calculation. Several useful information can be extracted here. The mean value of weighted reading literacy is 380.8 with standard deviation of 60.6. The score is considered low compared to neighborhood countries (Thailand average score is 393, Malaysia is 415, Brunei Darussalam is 408, and Singapore is 549) (OECD 2019). The deviation is large enough since there are 253 schools scored less than Thailand average and only 2 schools scored more than Singapore average. Large deviation was also found in SCHSIZE variable, since only one school having 10 students and 91 schools having more than 2,000 students. The average class size is 30.5, slightly more than OECD average, which is 23 students per class (OECD 2012). Another interesting fact is that the maximum number of STRATIO is 100, referring to 100 students for every one teacher. Regarding the ICT infrastructure, there are six schools which do not have computer and twenty-eight schools whose computers do not have access to the Internet. The good news is there are 217 schools whose all computers are connected to the Internet. For the qualitative variable, the proportion of public school participated in the assessment is 69.92%, the most among others.

Table 1. Descriptive statistics of the numerical variables used

Variables	Number of Schools	Mean	Standard Deviation	Min.	Max.
W_PV_READ	397	380.7786	60.62056	219.8723	583.4158
W_ESCS	397	-1.472486	0.7638336	-3.637881	0.7814717
SCHSIZE	310	571.0548	426.2542	10	2423
CLSIZE	332	30.51506	12.05788	13	53
STRATIO	308	16.93641	8.812257	1.5385	100
STUBEHA	337	-0.6812466	1.057923	-3.4161	2.6328
TEACHBEHA	337	-0.3931629	1.070548	-1.9767	2.9888
RATCMP1	299	0.3623977	0.6229713	0	10
RATCMP2	304	0.8063589	0.348759	0	1

4.2 Parameter Estimation

To estimate parameters in Equation (1), sfcross command of Stata (Belotti et al. 2013) was used. This command extends the capability of the available official Stata command frontier. The general syntax for this command is: sfcross [space] *depvar* [space] *indepvars*, distribution(•) [space] usigma(•) [space] vsigma(•). Syntax *depvar* and *indepvars* denote dependent and independent variables, respectively. To estimate Model 1, the option distribution(hnormal)was used. After thirteen iterations, the parameters of Model 1 were estimated, which are shown in Table 2 (the second column). Notice that only five parameters were statistically significant at the 5% level, i.e., (Constant, W_ESCS, SCHSIZE, σ_u, and σ_v). The sign of the coefficients can be interpreted as follows. A positive coefficient indicates that as the value of the predictor increases, the expected value of the response variable also tends to increase, vice versa. The value of the coefficient signifies how much the expected value of the response variable alters given a one-unit shift in the particular predictor while holding other predictors constant. This property is crucial because it allows to assess the effect of each variable in isolation from the others. The positive sign of W_ESCS indicates as the higher the economic, social and cultural status of the school, the higher the PISA score the school will obtain. The positive sign was also found in SCHSIZE, but the magnitude is very small. The coefficients of usigma and vsigma which are statistically significant at the 5% level imply that inefficiency and statistical noise do present.

The option distribution(tnormal) was used to estimate parameters of Model 2. After thirty-four iterations, the parameters were estimated, which are shown in the third column of Table 2. Note that similar to Model 1, Constant, W_ESCS, and SCHSIZE are all statistically significant at the 5% level. However, coefficients of μ and σ_u are not statistically significant (*p-value* = 0.815 and 0.614, respectively). It implies that inefficiency does not present in the model assuming truncated-normal distribution.

To estimate parameters in Model 3, the option distribution(exponential) was used. After nine iterations, the parameters were estimated, which are depicted in the fourth column of Table 2. Similar to Model 1 and Model 2, Constant, W_ESCS, and SCHSIZE are all statistically significant at the 5% level. However, unlike Model 2, inefficiency and statistical noise present since the coefficients of usigma and vsigma are statistically significant.

Finally, Model 4 can be estimated by adding RATCMP1 and RATCMP2 to variable usigma, while the distribution option follows Model 1. After thirteen iterations, the parameters were estimated, which are shown in the last column of Table 2. Similar to other models, Constant, W_ESCS, and SCHSIZE are all statistically significant at the 5% level. One of two determinants of inefficiency was statistically significant, i.e., RATCMP2. It means that the inefficiency is affected by the ratio of computers that were connected to the Internet.

Table 2. Parameter estimates of Model 1, 2, 3, 4

Variables	**The Half-normal Model**	**The Truncated-normal Model**	**The Exponential Model**	**The Heteroscedastic Model**
Constant	6.128463*	6.108812*	6.105879*	6.106835*
W_ESCS	0.1154871*	0.1182002*	0.1184893*	0.1174025*
SCHTYPE:				
Private indep.	6.90e-16	1.84e-16		4.00e-16
Private gov.	0.192738	0.0280054	0.0283818	0.0247837
Public	0.0272308	0.303799	0.0306109	0.0367162
SCHSIZE	0.0000755*	0.000073*	0.0000728*	0.0000775*
CLSIZE	-0.0002195	-0.000263	-0.0002573	-0.0002458
STRATIO	0.0005291	0.0004234	0.0004176	0.0005802
STUBEHA	-0.0110349	-0.0115962	-0.0115492	-0.115266
TEACHBEHA	0.0075445	0.0075794	0.0076202	0.0097859
μ		-1.78363		
σ_u	-4.126666*	-1.910426	-5.223357*	-3.380956*
RATCMP1				-1.378114
RATCMP2				-0.8897498*
σ_v	-5.129094*	-5.037458*	-5.013905*	-4.932457*

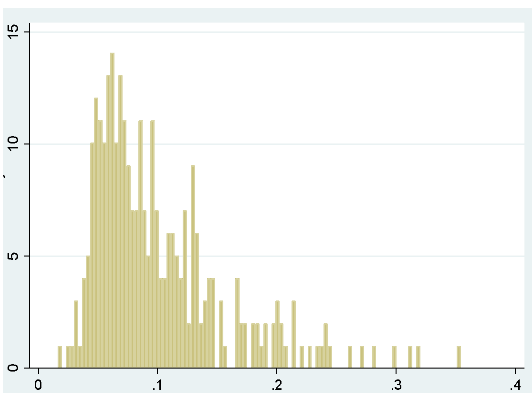
4.3 Inefficiency and Efficiency Estimation

The individual inefficiency was obtained by using Stata syntax predict [space] *newvar*, u. Since the coefficients of the composed error of Model 2 are not statistically significant, this model is discarded from further analysis. For Model

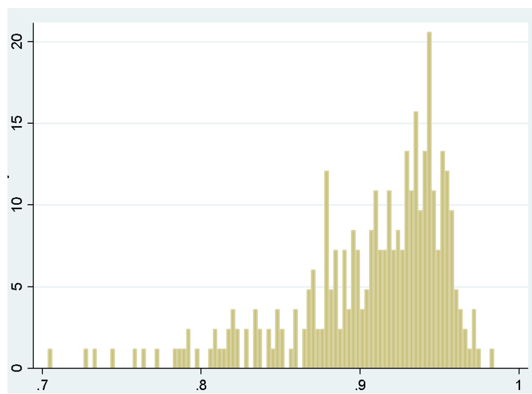
1, the average value of JLMS estimator is 0.1008, meaning that on average, the sampled schools lost about 10.08% of their potential output due to technical inefficiency. The individual efficiency can be found by using Stata syntax predict [space] *newvar*, bc. The option bc specifies the BC estimator. The mean of the efficiency is 0.9067, meaning that on average, schools achieve about 90% of the maximum potential output (measured by PISA reading score). The least efficient school achieves only 70.34% of the maximum potential output, while for most efficient school, about 2% of the maximum potential output is lost due to inefficiency. Note that the discrepancy between inefficiency and efficiency is due to the fact that $1 - \exp(u) \approx u$; and the approximation is close when u is small. The summary of the inefficiency and efficiency estimation of Model 1 are shown in Table 3 (the second to the fourth columns). Analogously, the summary of JLMS and BC estimators for Model 3 and Model 4 are also shown in Table 3. The histogram of individual inefficiency as well as individual efficiency for Model 1, Model 3, and Model 4 are shown in Figure 1. Notice that the histograms have skewed distribution. Another important consideration is that unlike DEA, there is no observation which has efficiency value equals to 1 (one). The rationale behind this condition is that in SFA, the deviation from the frontier is not only due to inefficiency, but also due to statistical noise (i.e., v_i).

Table 3. Inefficiency and efficiency estimation

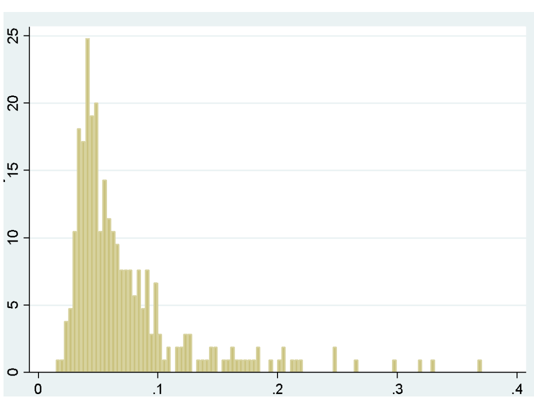
Estimators	Model 1			Model 3			Model 4		
	Mean	**Min.**	**Max.**	**Mean**	**Min.**	**Max.**	**Mean**	**Min.**	**Max.**
JLMS	0.1008	0.1061	0.3540	0.0734	0.0142	0.3704	0.0830	0.0001	0.3088
BC	0.9067	0.7034	0.9841	0.9316	0.6927	0.9860	0.9223	0.7363	0.9998



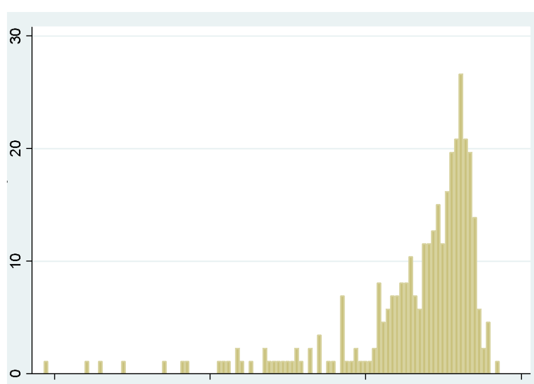
(a) Individual inefficiency of Model 1



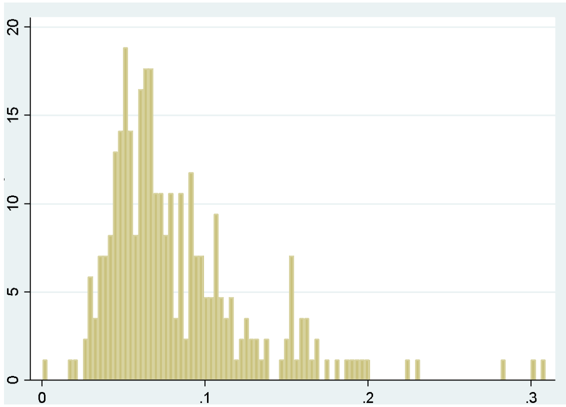
(b) Individual efficiency of Model 1



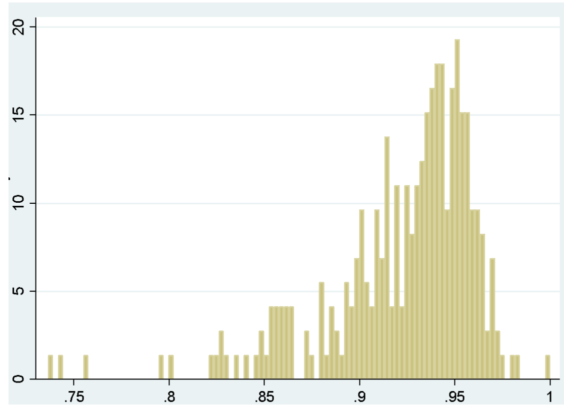
(c) Individual inefficiency of Model 3



(d) Individual efficiency of Model 3



(e) Individual inefficiency of Model 4



(f) Individual efficiency of Model 4

Figure 1. Histograms of individual inefficiency and individual efficiency for Model 1, 3, 4

5. Conclusion and Future Research Direction

This study has demonstrated how to measure inefficiency as well as efficiency by applying SFA. Data from OECD PISA 2018 only for Indonesian schools was used in this research. This study models the data into four different models considering the distribution assumption of inefficiency, namely, Model 1: half-normal model, Model 2: truncated-normal model, Model 3: exponential model, and Model 4: heteroscedastic model. Results showed that from seven independent variables, only index of school's economic, social and cultural status as well as school size were statistically significant at the 5% level. Moreover, Model 3 is considered as irrelevant since coefficients of the parameters of truncated-normal distribution are not statistically significant, implying that inefficiency does not present. For the heteroscedastic model, one can conclude that inefficiency is affected by the ratio of computers that were connected to the Internet.

For the future research, it is encouraged to conduct efficiency analysis for neighborhood countries (e.g., Singapore, Malaysia, Brunei Darussalam, and Thailand) and compared the results with this result. Also, by using panel data, a more promising research can be performed. Panel data contains more information than a single cross section data since the observations are observed repeatedly. The modeler can take into account some heterogeneity that may exist, which cannot be measured if one uses cross-section data. Another key advantage of using panel data is that it enables the modeler to examine whether inefficiency has been persistent over time.

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