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Measurement of Education Effectiveness in the BRICS countries and Turkey

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Abstract

The high literacy rate in a country shows that educational attainment is progressing well and efficiently. In this study, we aim to compare the effectiveness of education in the BRICS countries - Brazil, India, Russia, China, South Africa - and Turkey. We use the Stochastic Frontier Analysis method to measure the technical efficiency of education. The study utilizes 2017 and 2018 data, and linear functions to examine technical efficiency. The dataset comprises cross-sectional data. As a result, South Africa and India show the lowest technical efficiency scores, followed by China. Russia, Brazil, and Turkey scored high on technical efficiency for 2017 and 2018. This means that education levels in South Africa and India are unequal and shared among all residents. The 2017 and 2018 productivity scores are the same at 0.99% in Turkey, Russia, and Brazil. India's productivity score increased by 0.10% to 0.55% in 2018. Likewise, the productivity score calculated for China decreased by an average of 0.07 percent to 0.70 percent. However, South Africa's productivity score fell by 0.08 percent to 0.01 percent in 2018.

Keywords

Education effectiveness, technical efficiency, BRICS countries, Turkey, literacy rate

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Medición de la Eficacia de la Educación en los Países BRICS y Turquía

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Resumen

La alta tasa de alfabetización en un país muestra que el nivel educativo está progresando bien y de manera eficiente. En este estudio, nuestro objetivo es comparar la eficacia de la educación en los países BRICS (Brasil, India, Rusia, China, Sudáfrica) y Turquía. Utilizamos el método de Análisis de Frontera Estocástica para medir la eficiencia técnica de la educación. El estudio utiliza datos de 2017 y 2018 y funciones lineales para examinar la eficiencia técnica. El conjunto de datos comprende datos transversales. Como resultado, Sudáfrica e India muestran los puntajes de eficiencia técnica más bajos, seguidos de China. Rusia, Brasil y Turquía obtuvieron puntuaciones altas en eficiencia técnica en 2017 y 2018. Esto significa que los niveles educativos en Sudáfrica y la India son desiguales y compartidos entre todos los residentes. Los puntajes de productividad de 2017 y 2018 son los mismos (0,99%) en Turquía, Rusia y Brasil. La puntuación de productividad de la India aumentó entre un 0,10% y un 0,55% en 2018. Asimismo, la puntuación de productividad calculada para China disminuyó en un promedio de entre un 0,07% y un 0,70%. Sin embargo, el puntaje de productividad de Sudáfrica cayó entre un 0,08 por ciento y un 0,01 por ciento en 2018.

Palabras clave

Efectividad educativa, eficiencia técnica, países BRICS, turquía, tasa de alfabetización

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The effectiveness of education is defined as a systematic study to evaluate the level of realisation of the objectives of education, the benefits gained from education, the value of education, the development opportunities and the performance of those responsible for education (Eroğlu, 2006). From the beginning of the studies to the determination of the educational needs, the educational programme meets the people in need. It is known that the studies conducted to measure the effectiveness of education have three dimensions (Eroğlu, 2006). The first dimension is the evaluation of the design and development of education, the determination of the level of educational needs, and whether the training programme can be implemented as planned. The second dimension includes the measurement of training outcomes for each training programme. The last dimension relates to the effectiveness of the education system.

In order for the educational activity to be carried out successfully, the structure, functioning and characteristics of the education system should be determined. It should be determined which elements are of critical importance, and the problems and solutions that may be encountered should be identified.

Efficiency in education is generally measured by the ability to produce the maximum educational product with the minimum input (financial resources or the innate abilities of students). This measure of efficiency, called technical efficiency, is explained by a decrease in the amount of input when the amount of output is constant, or an increase in the amount of output when the amount of input is constant. According to the principle of SFA, technical efficiency can be represented by the gap between the actual output level and production frontier (Song & Chen, 2019).

One of the most important factors affecting the effectiveness of education is the number of qualified teachers. Increasing the number of qualified teachers has become the primary task of countries wishing to achieve quality in education. Efficiency in education is provided by professional teaching staff, and professional quality is ensured by increasing the number of teachers based on scientific principles (Kayadibi, 2012).

The importance and measurement of the concept of efficiency was first introduced by Farell (1957). Efficiency shows how well all the resources used in the production process are utilised. For all types of goods and services sectors in which production takes place, the success in obtaining the maximum output through the fully efficient use of the available inputs is called technical efficiency (TE) (Avcı, 2016).

At this point, the question of how to measure efficiency arises. Methods of measuring efficiency are examined under 3 headings: ratio analysis, non-parametric methods and parametric methods. The easiest method to apply with one input and one output is ratio analysis. One of the most widely used non-parametric methods is the Data Envelopment Analysis (DEA) method. This method is particularly important in sectors with many inputs and outputs, such as banking. Among the parametric methods, the most used are regression analysis, stochastic frontier analysis, distribution-free approach and thick frontier approach.

In the second part of the study, studies in the literature are included. In the third chapter, the theory of the Stochastic Frontier Analysis method is explained. The fourth chapter provides information on the variables and method to be used in the study. Finally, the fifth chapter presents the results of the application and discusses the findings.

Literature Review

A review of the literature shows that stochastic frontier analysis has been applied in various fields such as health, education, finance, production, agriculture, banking and economic performance. These studies differ not only in the choice of functional form, but also in the distributional assumptions and hence the determinants of inefficiency.

Aigner and Lovell (1977) used labour, materials and the gross book value of the plant as inputs and the ratio of materials to the net book value of the plant as outputs and the unit cost variable. This study uses 1957-1958 data from 28 companies in the US base metals industry. The Cobb-Douglas production function was used to estimate industry output using cross-sectional data. Monte Carlo simulation was used and the results were not sufficient. Even if the sample size for parameter estimation is as large as 100, it is difficult to estimate using the maximum likelihood technique. It was based on the study of Farell (1957), but the frontier function was not sufficient for various reasons. The use of the stochastic frontier generation function and the normal-half-normal distribution has been used to overcome a major shortcoming of previous studies.

Battese and Coelli (1992), total irrigated and non-irrigated area, total labour hours, total number of bucks purchased or rented as input, total input costs as output, and total output value of paddy and other crops grown. The application used agricultural data from a village in India. The result is that if the farmers' observation years are removed from the SFA, their technical efficiency does not change over time. A more detailed modelling of other variables affecting production and the statistical distribution of the random variables involved will lead to a better analysis of production and to better decisions regarding productive activity Battese and Coelli (1995), total irrigated and non-irrigated area as inputs, the proportion of irrigated land used, total hours worked, total number of bucks bought or rented, total input costs. The output is the total value of the farmers' output. Stochastic frontier production function panel data analysis was carried out using 10-year data from 14 paddy fields in India. It was concluded that the variables used in the application provide a data set that changes technical efficiency over time and is suitable for the inefficiency effects model. It was found that the fixed period, age, education level of the farmers and the years of observation are an important element of the SFA. The application also shows that the model properties allow for the estimation of both technical change and technical inefficiency that changes over time. Further theoretical and applied work is needed to obtain better models of technical inefficiency effects in the context of stochastic frontier and panel data analysis.

Robst (2001), using the translog cost function for higher education institutions in South Carolina, found that universities with a lower state share are not more efficient than universities with a higher state share. Stevens and Stevens (2001), evaluated the cost-effectiveness of a group of English and Welsh universities and emphasised that they are inefficient in the higher education sector. Izadi et al. (2002), use SFA dary estimation techniques to estimate a CES cost function under the assumption of a zero mean half-normal distribution of efficiency and have shown that there are significant inefficiencies in the UK higher education system.

Malighetti (2010) examines how the intensity of competition between airports affects the technical efficiency of airports by calculating their markets using a potential demand approach. The intensity of competition is found to have a negative impact on the efficiency of airports in

Italy over the period 2005-2008. This means that airports belonging to a strong local air transport system use their inputs less intensively than airports with local monopoly power. Furthermore, public airports were found to be more efficient than private and mixed airports. Dagbashyan (2011), Cobb-Douglas used the cost function form in his study of the cost-effectiveness of higher education institutions in Sweden. He found that universities in Sweden could not show the same efficiency performance, and their efficiency scores did not change much in the specified years, but their average efficiency scores were high. The effectiveness of the use of the SFA method by higher education institutions in Turkey and/or studies examining cost-effectiveness have remained very limited. Atılgan (2012) used the variables of total number of doctors, total number of medical assistants, total number of other employees and total number of beds as inputs in his study. The total number of outpatients was used as the output. A panel data model was used. In this study, the efficiency of hospitals was examined using the stochastic frontier analysis method with data from 429 hospitals between 2012 and 2014. Among the variables, the total number of beds was not statistically significant. University hospitals were found to be more inefficient than other hospitals. The optimal hospital capacity was found to be between 200 and 399. Accordingly, Erkoç (2015) examined the cost-effectiveness of 53 public universities in Turkey using the Cobb-Douglas and translog cost functions. The results of the study showed that the average efficiency performance of Turkish state universities was rather dispersed. Peresetsky and Kumbhakar (2013) used two models in their study. In model 1, labour and fixed capital funds are used as inputs. The loan amount variable is used as the output. In Model 2, Labor and Fixed Capital Funds variable is used as input and loan amount, collateral amount and borrowing amount are used as output. The model uses panel data. In this study, the cost efficiency of banks in Kazakhstan and Russia has been estimated using data from 2002 to 2006. Translog generation function is used in the model. The STATA programme was used to estimate the model. As a result, model 2 showed higher cost-effectiveness than model 1. Although most of the banks in both countries are below the optimal level, they tend to approach cost optimisation. Chen et al. (2014), The fuel capital stock is used as an input and the amount of electricity produced is used as an output. A fixed effect stochastic frontier model has been studied. This model was developed by Greene. The estimator of the linear regression model and the maximum likelihood estimator are consistent. The inconsistency is entirely due to the error variable. Greene's simulation states that the fixed effect SFA model is correct. The study suggests that the maximum likelihood estimator is based only on the common density deviation from the mean. The two models do not give the expected results. The SFA model gives a very high degree of inefficiency. This is because there is a heterogeneity effect in addition to the estimated inefficiency. Babita (2018) used the SFA method to measure the production efficiency of special economic zones in India, which is one of the types of free zones. The study considered panel data for the years 2009-2015 and identified three independent variables / inputs and one dependent variable / output. The amount of raw materials, capital and labour were selected as independent variables and the volume of exports generated by the regions as the dependent variable. The study found that the Cobb-Douglas production function was preferable to the translogo production function. The relationship between technical inefficiency and variables was shared by making and interpreting parameter estimates.

Liu et al. (2021) measure industrial land use efficiency (ILUE) in China using the stochastic frontier analysis (SFA) method. A translog SFA model describing the relationship between industrial land productivity and land input level was established to estimate productivity. According to the analysis results, it was determined that the stochastic frontier method was suitable for ILUE measurement and the contribution rate of the technical inefficiency term to the mixed error reached 66.9%. According to the results of the inefficiency function, it was determined that the business ownership structure had a negative impact on ILUE. While the specialization of the high-tech manufacturing industry, the level of urbanization and transportation conditions have a positive impact on ILUE, the specialization of the chemical and rubber industry and local financial pressure have a negative impact.

Koengkan et al. (2022), analyzes the economic productivity performance of 14 countries from the Latin America and Caribbean (LAC) region for the years 1990-2017. Parametric stochastic frontier analysis (SFA) and non-parametric data envelopment analysis (DEA) were used to analyze the economic performance of these countries with linear Cobb-Douglas production. Both approaches show that Panama is the most economically productive country in the LAC region, followed by Chile. The results show that Brazil (SFA) and Nicaragua (DAE) are the least economically productive LAC countries.

Workneh and Kumar (2023), this study attempted to measure the technical efficiency of large-scale agricultural investment in Northwest Ethiopia. To this end, it uses the stochastic frontier approach to estimate technical efficiency based on cross-sectional data of 200 investors. The study found that better use of capital, labour, land and seed inputs had a positive impact on grain production. It found that the overall average technical efficiency was 71.7%, meaning producers produced approximately 28.3% of grain due to technical inefficiency.

Mbah and Agu (2024) this study evaluated the level of technical efficiency in Nigerian manufacturing companies and examined the determinants of technical inefficiency. Stochastic Frontier Analysis was conducted using panel data of fifty-five manufacturing companies traded on the Nigerian Stock Exchange Market between 1999 and 2020. As a result, it has been determined that all inputs (capital, labor, raw materials, energy costs and other expenses) are affected. It is positive on firms' output at the 1% significance level. However, the impact of the raw material is the highest. The average productivity of Nigerian manufacturing companies was also found to be 52.74%. Finally, firm age, total assets and management efficiency were found to be determinants of technical inefficiency in Nigerian manufacturing firms. This means that the productivity level of manufacturing firms in Nigeria can be increased by 47.26%.

Methodology

Stochastic Frontier Analysis

Stochastic Frontier Analysis (SFA) is an approach used to estimate production frontier functions and measure efficiency to determine whether production is being carried out effectively in each production area. SFA is based on the logic of using econometric models to estimate the errors that occur in production and to minimise the inefficiency caused by these errors.

The starting point for SFA and efficiency measurement is the approach proposed by Farell (1957), there are two elements in measuring its effectiveness. The first is technical efficiency and the second is allocative efficiency. Technical efficiency; it is a criterion for determining the maximum level of output that a country can obtain from existing inputs. Allocative efficiency; While the prices of inputs are available, it indicates the ability of the country to use these inputs at the appropriate rate (Avcı, 2016). The technical efficiency and allocative efficiency measures assume that the production function of fully efficient countrys is known. The total efficiency score is obtained by considering these technical and allocative efficiency concepts together and multiplying them mathematically (Farell, 1957).

Stochastic Production Frontier Function

Stochastic frontier models are often used in the literature to achieve maximum profit, minimum cost production, maximum revenue and production target. Aigner and Lovell (1977) and Meeusen and Broeck (1977) proposed the stochastic production frontier function, which they developed independently and at the same time as follows:

$yi = f(xi\ ,\ \beta i\ ) + vi - ui = f(xi\ ,\ \beta i\ ) + \varepsilon_i$

Here,

y_i : i. the amount of output of the decision-making unit

x_i : xi: k * 1 dimensional vector showing the inputs of the i.

β_i : Unknown parameter vector

v_i : Independent and random variable showing the distribution of $N(0,\sigma_i^2)$

u_i : Non-negative random variable indicating technical ineffectiveness

The stochastic production frontier model assumes that ε_i is a combined error consisting of two independent variables denoted by u_i and v_i. The random variable v_i can be either negative or positive. Using the SFA function, TE is obtained as follows (Avcı, 2016):

$$yi = f(xi\ ,\ \beta i\ ) * TE$$
$$TE = yi\ /\ f(xi\ ,\beta i\ ) = e^{-ui}$$

The technical efficiency score is equal to 1 if maximum output is obtained with minimum input or production at full efficiency, otherwise it is less than 1.

When random errors ($\varepsilon_i = v_i - u_i$) are added to the model in SFA, TE is written as follows (Kumbhakar & Lovell, 2000);

$$y_i = f(xi\ ,\ \beta i * e^{vi}) * TE$$
$$TE = y_i \setminus f(xi\ ,\ \beta i * e^{vi})$$

The assumptions of stochastic frontier analysis are the same as those of the classical linear regression model. The term ineffectiveness also has similar assumptions, but since $ui \geq 0$, its mean is not zero (Coelli et al., 2005).

Linear, log-linear, Cobb-Douglass, translog, constant elasticity of substitution (CES) or non-linear functions can be used to investigate technical inefficiency. Linear, Cobb-Douglass and Translog functions are most commonly used in practice. In this study, linear functions were used to investigate technical efficiency.

The generalised C-D generation function for the stochastic frontier model in the literature is shown below;

$$\ln y_{it} = \beta_0 + \sum_{j=1}^{N} \beta_j \ln (x_{it}) + v_i - u_i$$

y_{it} : logarithmic production status for i. country and t.time
x_{it} : the load vector required for i. country and t.time
β_i : Parameters (i=1,2,..n)
u_i : Random residuals (error terms)
N : Number of entries

The purpose of the production function above is to predict the vector β, which defines the structure of the production frontier function, and u_i (random errors), which are used to determine technical efficiency. Since there are two error terms ($\varepsilon_i = v_i - u_i$) on the right-hand side of the equation, the estimation of the parameters is difficult.

Consistent estimates of the slope parameters βj can be obtained using the EKK method, but when the inefficiency term has a mean greater than zero, the intercept coefficient estimate of β_0 is biased because $E(\varepsilon_i) = -E(u_i) \leq 0$. Therefore, it is recommended to use the COLS or MOLS method instead of this method (Kumbhakar & Lovell, 2000).

The distribution of the error term u_i, which indicates technical inefficiency, is still a matter of debate. In the generalised Cobb-Douglass production function for the stochastic frontier model, the random error term v_i is assumed to have a mean of 0, a constant variance and a normal distribution independent of u_i. The technical inefficiency error term is generally assumed to have normal half-normal, normal exponential, normal gamma and normal truncated normal distributions.

For the stochastic frontier model, technical inefficiency effects can be tested. The one-tailed generalised likelihood ratio test is used to predict the model under defined hypotheses. This test statistic, known in studies as the likelihood ratio (LR) test, is calculated as follows:

$$LR = -2\{\ln[L(H_0)] - \ln[L(H_A)]\}$$

In test statistics, $L\,[H_0]$ and $L\,[H_A]$ are the values of the likelihood function obtained under the null and alternative hypothesis.

In practice, the likelihood ratio statistic is used to test whether there is technical inefficiency in the model under consideration. It is also compared to the table value of 2.706, which is a restricted Kodde-Palm table value at the 0.05 significance level. The hypothesis for the LR statistic is as follows:

$$H_0: \lambda = 0$$
$$H_a: \lambda > 0$$

Since the LR statistic is greater than the value of the Kodde-Palm table, the hypothesis H_0 is rejected and there is statistically significant technical inefficiency in the model. When $\lambda = 0$ in the hypothesis created for the parameter "γ" used by Battese and Corna (1977), this statistic is asymptotically distributed like the standard normal random variable. λ It should be tested unilaterally as it will only take positive values.

Data Set and Method

In this study, the Stochastic Frontier Analysis approach was used under the assumption of half-normal distribution by using the 2017 and 2018 cross-sectional data to measure the educational effectiveness in BRICS countries and Turkey. For this purpose, countries' literacy rates (young adults aged 15 and above) were used as dependent variables, gross primary school enrolment rate (percentage of primary school age population), pupil-teacher ratio (primary school, pupils per teacher), number of young people not attending school or working (15-24 years), population with at least secondary education (25% and above) were used as independent variables. The Stata 14.0 package was used for the analysis. Rstudio was used to visualise the correlation relationships between variables and to obtain summary statistics of the technical efficiency scores. Given the available data, the half-normal model was estimated and the efficiency scores of the countries were compared.

The variables used in the model are as follows:

Literacy rate (young adults aged 15 and over)	**OKR**
Gross enrolment rate in primary education (% of population of primary school age)	**KO**
Pupil-teacher ratio (primary school, pupils per teacher)	**OGR**
Number of young people not in education or employment (15-24 years)	**OKL**
Population with at least secondary education (25% and more)	**OEGT**

Findings

Firstly, summary statistics of the variables were obtained and presented in Table 1.

Table 1

Descriptive Statistics

	2018					
	Maximum	**Minimum**	**Mean**	**Median**	**1st.deviation**	**3st.deviation**
OKR	99.70	74.40	91.22	94.70	88.55	96.65
KO	115	93	104.2	102.0	100.2	110.5
OGR	33.00	16.00	22.83	20.50	17.75	27.75
OKL	31.60	14.60	23.82	24.25	19.38	28.95
OEGT	95.90	39.20	68.25	67.90	60.08	77.83

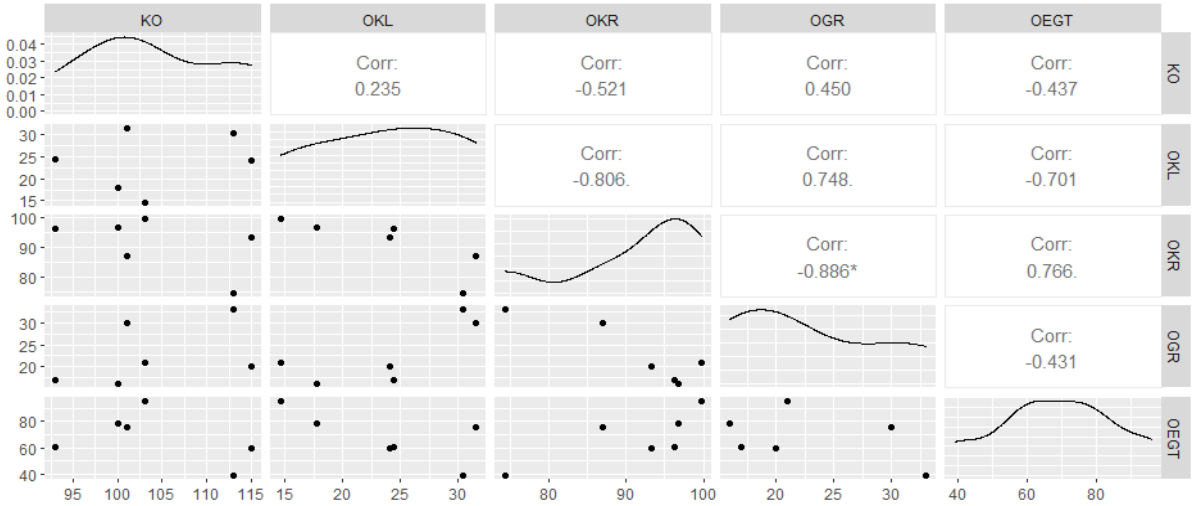
	2017					
	Maximum	**Minimum**	**Mean**	**Median**	**1st.deviation**	**3st.deviation**
OKR	99.78	91.66	97.56	99.43	96.28	99.74
KO	99.40	86.01	91.95	91.50	87.23	96.00
OGR	32.75	14.60	20.40	18.60	16.69	21.00
OKL	31.01	12.41	23.25	24.26	18.93	28.89
OEGT	95.80	39.30	67.54	66.61	59.56	76.43

According to the 2018 results, the highest mean, standard deviation and median values belong to literacy rate and primary school enrollment rate variables. 1 The standard deviation values of the literacy rate and primary school enrolment rate variables were calculated as 88.55 and 100.2, respectively. In 2017, the highest mean, standard deviation and median values belong to the variables of literacy rate and primary school enrolment rate. The 1 standard deviation values of the literacy rate and primary school enrolment rate variables were 96.28 and 87.23, respectively. The fact that the standard deviation is so large means that the variable is not homogeneously distributed. This rather high value also indicates that the variable has a distribution far from its mean. The average value of the literacy rate in 2018 was 91.22 and the median was 94.70. Similarly, the average value of the variable primary school enrolment rate was 104.2 and the median value was 102.0. The average value of the literacy rate in 2017 was 97.56 and the median value was 99.43. Similarly, the average value of the primary school enrolment rate variable was 91.95 and the median was 91.50. The fact that the median, also expressed as the mean, is so close to the mean indicates that the variable has an almost symmetrical distribution.

The correlation relationships between the variables are visualised with the Pearson correlation coefficient as follows.

Figure 1

Correlations Between Variables for 2018



According to Figure 1, there is a negative and moderate correlation of -0.521 between the enrolment rate and the literacy rate. There is a weak positive correlation of around 0.235

between the enrolment rate and the proportion of young people who are not in school or not working. There is a strong positive correlation of 0.748 between the pupil-teacher ratio and the proportion of young people not attending school or not working.

Figure 2

Correlations Between Variables for 2017

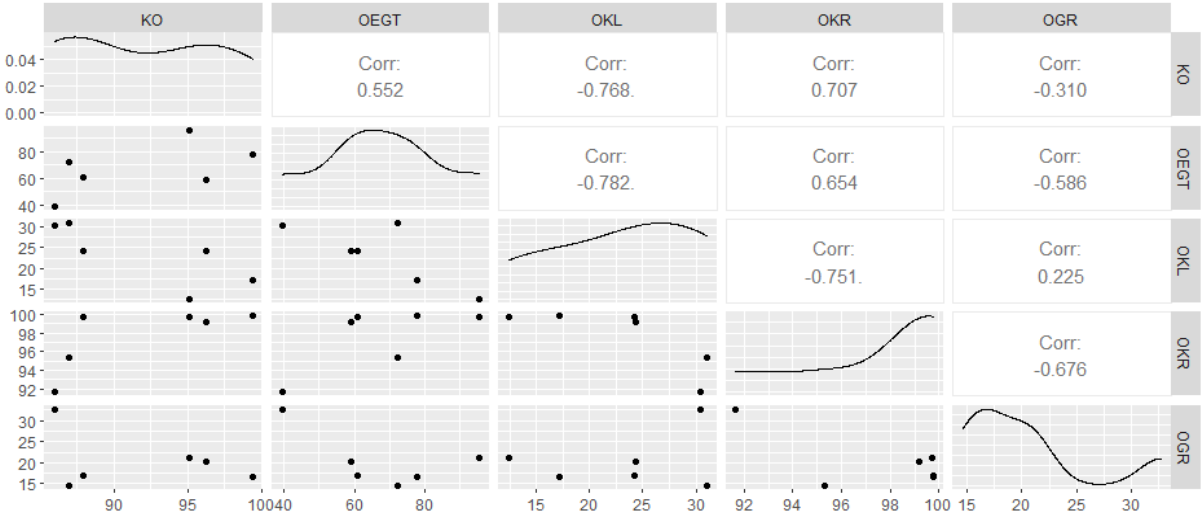


Figure 2 shows that there is a positive and strong correlation of 0.707 between the schooling rate and the literacy rate. There is a strong inverse correlation of -0.768 between the schooling rate and the proportion of young people who are neither in school nor working. There is a weak positive correlation of 0.225 between the pupil-teacher ratio and the proportion of young people not attending school or not working. Similar observations can be made between other variables. Table 2, Shows the Results of the Stochastic Frontier Analysis Using the Half-Normal Model.

Table 2

Stochastic Frontier Analysis Results (Half-Normal Model)

Variables	**2018**		**2017**	
lnOKR	**Coefficients**	**P>|z|**	**Coefficients**	**P>|z|**
lnOEGT	.1129014	0.035	-.138854	0.000
lnKO	.0263594	0.013	.0784696	0.000
lnOGR	-1.068595	0.000	-.4383552	0.000
lnOKL	-.3278653	0.000	-.5188251	0.000
Constant	112.9406	0.000	121.2962	0.000
lnsig2v	-27.77048	0.017	-29.27439	0.017
lnsig2v	1.179673	0.041	.0142858	0.031
Sigma_v	9.33e-07		4.40e-07	
Sigma_u	1.803693		1.007168	
Sigma2	3.253309		1.014388	
Lambda	1933957		2290628	
Prob	0.000		0.019	

Variables	2018	2017
Wald	3.46e+07	2374394.08
LogLikelihood	7.8937671	4.3976076

According to the results obtained for 2018, the explanatory variables were found to be statistically significant. A 1% increase in the proportion of the population with at least secondary education increases the literacy rate by 0.11%, and a 1% increase in the primary enrolment rate increases the literacy rate by 0.02%. A 1% increase in the pupil-teacher ratio will reduce the literacy rate by 1.07%, and a 1% increase in the rate of young people not in school or work will reduce the literacy rate by 0.33%.

$$\ln OKR = 112.9406 + 0.1129014 \ln OEGT + 0.0263594 \ln KO - 1.068595 \ln OGR - 0.3278653 \ln OKL + \varepsilon_i$$

If $\lambda = 0$, there is no technical inefficiency and deviations from the production frontier function are only due to random errors. The value of lambda (λ) obtained in the model is 0.1933579. Therefore, approximately 0.1933579 of the deviations in the production frontier function in the model are due to technical inefficiency (u_i) and the remaining part is due to random errors (v_i). According to the results obtained from the table, the LR value was found to be 7.8937671. The null hypothesis is rejected because it is greater than the value of the Palm table in the script. It is concluded that there is a statistically significant technical inefficiency in the model.

According to the results obtained for 2017, the explanatory variables were found to be statistically significant. A 1% increase in the proportion of the population with at least secondary education increases the literacy rate by 0.14%, and a 1% increase in the primary school enrolment rate increases the literacy rate by 0.07%. A 1% increase in the rate of student teachers will reduce the literacy rate by 0.43%, and a 1% increase in the rate of young people not in school or work will reduce the literacy rate by 0.52%.

$$\ln OKR = 121.2962 - 0.138854 \ln OEGT + 0.0784696 \ln KO - 0.4383552 \ln OGR - 0.5188251 \ln OKL + \varepsilon_i$$

The value of lambda (λ) obtained in the model is 0.2290628. Therefore, about 0.2290628 of the deviations in the production frontier function in the model are due to technical inefficiency (u_i) and the remaining part is due to random errors (v_i).

According to the results obtained from the table, the LR value was found to be 4.3976076. As a result, technical inefficiency was found in the model.

The technical efficiency values obtained for the half-normal model are shown in Table 3.

Table 3

Technical Efficiency Scores For The Half-Normal Model

Countries	Years	
	2017	**2018**
Brazil	0.9999977	0.9999949

Countries	Years	
	2017	2018
Russia	0.9999977	0.9999952
India	0.4544772	0.5547581
South Africa	0.0980244	0.012727
China	0.7671774	0.6993198
Turkey	0.9999976	0.9999952

According to the technical efficiency scores obtained in 2017, the country with the lowest technical efficiency value is South Africa with 0.09%. The countries with the highest score are Brazil, Russia and Turkey with 0.99%. China is in second place with 0.77% and India is in third place with 0.45%.

According to the values obtained for the year 2018, Brazil, Russia and Turkey still rank first with an efficiency score of 0.99%. China ranks second with an efficiency score of 0.70%. India ranks third with 0.55% and South Africa ranks last with 0.01%.

2017 and 2018 in Turkey, Russia and Brazil in efficiency scores are the same. India's efficiency score increased by 0.10% in 2018 to reach 0.55%. Similarly, the efficiency score calculated for China decreased by an average of 0.07%, reaching 0.70%. However, South Africa's efficiency score decreased by 0.08 percent in 2018, reaching 0.01 percent.

The summary statistics for technical efficiency are shown in Table 4.

Table 4

Summary Statistics for Technical Efficiency

Descriptives Statistics	2017	2018
Numberof Observations	6	6
Mean	0.71995	0.71113
Minimum	0.09802	0.01273
Maximum	1.00000	1.00000
Median	0.88359	0.84966
1std.dev.	0.53265	0.59090
3std.dev.	1.00000	1.00000

According to the results of the table, while the mean value of the term technical efficiency was 0.72 for 2017, it was 0.71 for 2018. While the median was 0.88 for 2017, it was 0.85 for 2018. Similarly, while the minimum value calculated for technical efficiency was 0.10 for 2017, it was 0.01 for 2018.

As a result, the countries of India and South Africa could not achieve educational effectiveness, as they were below the average of the technical efficiency score calculated in 2017 (0.72). Similarly, education efficiency could not be achieved in China, India and South African countries, which were below the mean of the technical efficiency score (0.71) calculated for 2018.

Conclusión

Today, the development of education and training programmes is of paramount importance. Well-prepared programmes and methods are needed for teaching to result in education. With a well-prepared programme, you can achieve the desired goals and quality in education and training. In a constantly changing world, educational programmes and methods should be prepared in accordance with innovations. It is necessary to monitor internal and external factors affecting the education system in a planned and systematic way.

In order for the educational system to function properly and effectively, it is necessary to determine the training needs correctly, fulfil the training in a planned and systematic way, act according to the principle of equal opportunities in education, and provide training that is compatible with the vision, mission, goals and strategies of the institution (Kayadibi, 2012). In this study, the aim is to measure the educational efficiency using the stochastic frontier analysis approach by using the data of 2017 and 2018 in BRICS countries and Turkey. By estimating the technical efficiency scores and statistical summary information, it is determined that the educational effectiveness cannot be achieved in the countries below the average of the technical efficiency term.

According to the technical efficiency scores calculated for 2018, Brazil, Russia and Turkey are in first place with a value of 0.99%. China is in second place with an efficiency of 0.70%. India is third with 0.55% and South Africa is last with 0.01%. It can be concluded that educational effectiveness cannot be achieved in China, India and South Africa, which are below the average of the calculated technical efficiency. For 2017, the lowest technical efficiency value according to the technical efficiency scores obtained for 2017 is South Africa with 0.09%. The highest countries are Brazil, Russia and Turkey with a value of 0.99%. China is in second place with 0.77% and India is in third place with 0.45%. Educational efficiency could not be achieved in the countries of India and South Africa, which are below the average of the calculated technical efficiency.

As a result, Turkey, Russia and Brazil had the same efficiency scores in 2017 and 2018. India's efficiency score increased by 0.10% in 2018, reaching 0.55%. The efficiency score calculated for China was 0.70%, with an average decrease of 0.7%, while South Africa's efficiency score decreased by 0.8% in 2018 and was found to be 0.01%.

In reviewing the studies in the literature, the majority of studies have been conducted to measure the efficiency of universities. However, in this study, efficiency comparisons have been made on a country basis by considering mostly primary, secondary and tertiary indicators. In this respect, it differs from many studies in the literature.

Thanks to the variables used in this study, such as gross primary school enrolment rate, pupil-teacher ratio, out-of-school and unemployed youth, and the proportion of the population with at least secondary education, administrators and policy makers should invest in these indicators to improve the efficiency of primary, secondary and tertiary education.

In order to successfully measure educational effectiveness, it is necessary to determine the structure of the educational system and the characteristics it should have. Elements of critical importance should be identified, and problems and solutions that may arise should be identified.

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