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Factors which Affect Productivity of Education Expenditure in Ethiopia: Evidence from Ethiopian Public Universities

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ABSTRACT

This article measures the productivity of Ethiopian public universities and identifies the factors that influence it. Using a quantitative research approach and secondary data, the study targeted Ethiopian public universities to assess their total factor productivity (TFP). The researchers used a non-parametric approach, specifically the Malmquist productivity index, to measure TFP performance. They then used a parametric approach, or multiple regression analysis, to examine the factors affecting TFP change. In this study total factor productivity change was used as a proxy to measure productivity of universities and pure efficiency, technical efficiency and scale efficiency were considered as independent variable. The findings showed an overall decline in university productivity over the study period. However, the analysis also revealed a positive trend of yearly productivity improvement. The study found that all selected variables—technical change, pure efficiency change, and scale efficiency change has a positive and statistically significant effect on the productivity of education expenditure. The researcher would like to suggest the university community to focus work on the efficiency improvement to enhance the productivity of the university.

1. INTRODUCTION

Higher education is essential for a country's economic development by equipping people with the necessary skills and knowledge for innovation and new ideas (Kipesha & Msigwa, 2013). Its goal is to create a well-trained workforce capable of sharing knowledge and raising professional standards. Investing in education is an asset in humanity's future. Ethiopia's higher education system, which began in 1943, has grown significantly. From just two universities in 1998, the number has expanded to 45, with over 479,000 students enrolled in regular programs alone. The Ministry of Science and Higher Education (2022) identifies education as a key sector for poverty reduction and fostering rapid, inclusive economic growth.

Despite this expansion, Ethiopia's productivity lags behind other industrializing nations like Myanmar, Vietnam, Cambodia, and Tanzania, whose productivity is between 1.7 and 3.4 times higher. According to a 2022 report by the Ethiopian Policy Study, recent gains in labor productivity in Ethiopia are primarily due to increased capital investment (capital deepening) rather than improvements in Total Factor Productivity (TFP).

A comparison using the International Labour Organization's (ILO) data shows that Ethiopia's labor productivity from 2000 to 2022 is at the low end of global and regional averages. In 2020, Ethiopia's labor productivity was only 40% of the average for Sub-Saharan Africa, a quarter of the average for lower-middle-income countries, and 10% of the average for upper-middle-income countries. This is a critical issue for policymakers, as productivity is a key driver of sustainable economic growth (Conway, 2016).

According to Growth Accounting Theory, labor productivity growth can be explained by improvements in labor quality, capital intensity, and TFP growth, which accounts for innovation and efficiency. Recognizing this, Ethiopia has made the pursuit of productivity a key policy direction under its Growth and Transformation Plan II (GTP II).

Productivity is a combination of effectiveness and efficiency. An organization is effective if it meets its goals and efficient if it uses its resources well. For a public sector organization to be productive, it must be both. According to Pollitt and Bouckaert (2004), public sector productivity can be increased in various ways, such as by reducing resources while increasing output, or by decreasing resources more than the decrease in output. Several countries, including the UK, Finland, and Australia, have established specific institutions to measure public sector productivity.

The Tornqvist index, developed by the American National Research Council (NRC), is a widely used and reliable model for measuring productivity, particularly in higher education. It's endorsed by the OECD and the U.S. Bureau of Labor Statistics. The index calculates productivity as the ratio of an output index to an input index, showing how much output changes relative to a change in inputs over time. Inputs: The model measures inputs in terms of total factor productivity, including monetary values for labor (employee expenses), capital (long-term assets), and intermediaries (operational and administrative expenses). Outputs: The NRC model includes several potential outputs for higher education, such as student load, coursework completions, graduate employment, and learning outcomes. For research, outputs can include publications, citations, patents, and research funds. This model provides a flexible framework that can be adapted to the specific accounting practices and priorities of different countries and institutions.

The research on Ethiopian public universities applies this base model to measure educational productivity. The study's approach, consistent with the engineering concept of productivity, focuses on the change in output relative to the change in inputs over time. The model identifies both quantitative and expenditure-based inputs. Outputs are measured by student credit hours and completions, such as degrees conferred to undergraduate and graduate students, often categorized by gender or other relevant groups. This methodology allows for a detailed analysis of how resource changes impact educational outcomes.

The Malmquist Productivity Index (MPI) is a DEA-based approach that measures productivity changes over time. Developed by Fare et al. (1994) and based on the earlier work of Malmquist (1953) and Farrell (1957), the MPI is a powerful tool for longitudinal analysis. In the context of education, productivity models aim to provide a conceptual blueprint for the complex factors that influence the quality and quantity of service output. The Asia Productivity Organization (APO) and the National Research Council (NRC) have developed productivity models, such as the Tornqvist index, which account for total factor productivity using inputs like labor, capital, and intermediaries. Outputs are typically measured by instructional outcomes, such as credit hours, degrees conferred, and graduation rates. Other measures of efficiency include ratios like instructional expenditure per student or enrollment per faculty member. The goal of improving productivity requires a focus on innovation, proper training, and a balance between management and service. It also requires a robust conceptual model and accurate data to measure and manage the entire system effectively. A 2011 study on OECD and Asian countries, which applied DEA to measure the efficiency of government spending, found that a strong conceptual model is essential for a meaningful analysis.

Organizational Productivity Dis-aggregating Model: This model breaks down the fundamental components of productivity—inputs, conversion technology, and outputs—into more detailed sub-classes. This approach allows for a more specific analysis of productivity at different levels within an organization, such as a university department versus the entire institution. It is rooted in the idea of viewing organizations as sociotechnical systems.

The fundamental economic theory that underpins productivity is Production Theory, which explains how inputs are converted into outputs. According to this theory, a rise in productivity is indicated by a shift in the production function, which reflects a better relationship between outputs and inputs. For a university, a productive one would show a significant increase in its graduation rate (output) relative to its student enrollment (input). This is a core concept for monitoring a university's long-term economic health and performance.

2. FACTORS WHICH AFFECT TOTAL FACTOR PRODUCTIVITY CHANGE

Research on the efficiency and productivity of public organizations is a well-established field, with studies spanning various sectors from tourism and healthcare to banking and education. The Malmquist productivity index and Data Envelopment Analysis (DEA) are two common modeling approaches used to measure these factors. For instance, a 2007 study by Cracolici, Nijkamp, and Cuffaro found no improvement in the competitiveness of Italian tourist destinations, while others have successfully applied these methods to assess the productivity of hospitals and banks.

In higher education, the core focus of productivity measurement is on teaching. The American National Research Council (NRC, 2019) and various studies confirm that teaching is a primary function for analysis. The most common output measures are the number of graduates from both undergraduate and postgraduate programs, as this is considered a key indicator of institutional accountability and performance. Some researchers, such as Hopkins and Massy (1981), define productivity as the change in graduation rates relative to the change in student enrollment over time.

To measure productivity, researchers use various inputs and outputs. Common inputs in higher education efficiency analysis include expenditures on labor, materials, and capital, as well as faculty and staff time, buildings, and library resources. Outputs are typically defined by student outcomes, such as degrees awarded and graduation rates. It is important to note, however, that while graduation rates are a simple and powerful metric, they have limitations, as they may not fully capture the quality of the education or account for students who drop out.

Beyond inputs and outputs, external factors can significantly influence an institution's performance. Environmental factors like institutional and structural conditions can affect efficiency. In a study on Swedish eye care services, Lothgren and Tambour (1999) used the Malmquist index to assess productivity, while a study on public schools in Andorra found that decentralization had a significant, positive impact on efficiency. Other studies have also identified specific variables that affect productivity, such as student enrollment, academic and non-academic staff numbers, and even the availability of school facilities and technology.

Globally, a key focus of research is the link between public spending on education and economic growth. A 2012 study by Muktdair-Al-Mukit on Bangladesh found that a 1% increase in public education expenditure led to a 0.34% increase in GDP per capita in the long run. However, simply increasing spending is not enough. Several studies, including one on EU countries by Aubyn, Garcia, and Pais (2009), conclude that these nations do not need to increase their spending but rather need to **spend more efficiently**. This highlights the importance of analyzing how resources are used and whether they produce the desired outcomes.

The concept of productivity itself is often broken down into two parts: **efficiency** (doing more with the same resources) and **effectiveness** (meeting the demands of customers, in this case, students, parents, and employers). Improving productivity involves strategies like increasing the flexibility and quality of faculty and using technology more efficiently. The ultimate goal is for higher education to produce well-educated, productive graduates who can drive a country's socio-economic development.

3. MEASUREMENTS

According to Coeli 1996b, total factor productivity changes are decomposed to technical change, pure technical efficiency change, and scale efficiency changes. Accordingly, this study has made a fixed effect panel regression analysis. This research question has answered the effect of technical change, pure efficiency changes, and scale efficiency changes on the total factor productivity of selected public universities. The dependent variable is total factor productivity changes obtained in the Malmquist productivity index using DEAP 2.1 software. The independent variables are changes in technical change, pure efficiency changes, and scale efficiency changes derived from the Malmquist productivity study.

The following hypothesis was formulated to test the effect of technical change, pure technical efficiency changes, and scale efficiency changes on the total factor productivity change.

Ho1: Technical change affects the total factor productivity change

H_a1: Technical change does not affect the total factor productivity change

Ho2: pure efficiency changes affect the total factor productivity change

H_a2: pure efficiency change does not affect the total factor productivity change

Ho3: scale efficiency changes affect the total factor productivity change

H_{a3}: scale efficiency change does not affect the total factor productivity change

Ho4: There is no relationship between expenditure efficiency and productivity of public universities

H_a4: There is a strong relationship between expenditure efficiency and productivity of public universities

This study analyzes the productivity of universities using the well-established Malmquist Productivity Index (MPI). Malmquist originally introduced the input distance function to compare consumption bundles, but the MPI was later developed by Färe, Grosskopf, Norris, and Zhang (1994) and Roos (1989, 1992) as a measure of total factor productivity change. To create a productivity indicator, the study devised a model that measured educational productivity through coursework completion, graduate employment, and credit hours. It also intended to measure research productivity using publications, citations, patents, research completions, and research funds. However, due to a lack of available data, the analysis of research productivity for public universities was ultimately excluded from this research.

$$m_o\ (y_{1+t}, x_{1+t},\ y_t, x_t) = \sqrt{\left[\frac{d_o^t(x_{t+1}, y_{t+1})}{d_o^t\ (x_t,\ y_t\ )}\right] x \left[\frac{d_o^{t+1}(x_{t+1,}Y_{t+1})}{d_o^{t+1}\ (x_t, y_t\ )}\right]}$$

This represents the productivity of the production point ($xt_{+1,\ yt+1}$) relative to the production point (x_t, y_t). A value; greater than one indicates

Productivity growth from period t to period t+1.

Productivity measurement model

According to Coeli (1996b), total factor productivity changes are decomposed to technical change, pure technical efficiency change, and scale efficiency changes. Accordingly, this study has used these variables to test the effect of efficiency changes on change in productivities of Ethiopian public universities, and a fixed effect panel regression model was applied.

This research question has answered the effect of technical change, pure efficiency changes, and scale efficiency changes on the total factor productivity of selected public universities. The dependent variable is total factor productivity changes obtained in the

Malmquist productivity index using DEAP 2.1 software. The independent variables are changes in technical change, pure efficiency changes, and scale efficiency changes derived from the Malmquist productivity study.

To measure the dependent variable (total factor productivity change) and independent variables like change in technical change, change in pure efficiency, and change in scale efficiency; the Malmquist index is selected because it decomposes efficiency changes into productivity growth, which to the best practice frontier improvements and efficiency growth that changes relative to the best practice frontier.

$$TFPCH = \beta0 + \beta1\text{TCHit} + \beta2\text{PECHti} + \beta3\text{SECHti} + \mu \ldots$$

Where TFPCH – is expenditure productivity measured based on the total factor productivity change result obtained from public Universities

β_0 – is the unknown constant of the equation to be estimated

β_1 and β_3 - are the unknown coefficients of the independent variables to be estimated

μ – is the error term of the regression equation

TCH_{it}: represents technical change at time t and university i

$PECH_{it}$: represent pure efficiency change at time t and university i

SECHti- represents scale efficiency change at time t and university i

TFPCH: total factor productivity change

The total factor productivity change was obtained using MPI; moreover, the technical change, pure efficiency changes, and scale efficiency changes are generated from the Malmquist productivity index based on selected multiple outputs and inputs of public universities.

To analyze the relationship among independent variables and to evaluate the effect of identified dependent variables on the total factor productivity change (dependent variable), a fixed effect panel data model was used in Stata 16.

The relation between education expenditure efficiency and productivity of public universities

This research question aims to answer what types of relationship exist between efficiency and productivity or what effect does efficiency has on the productivity of public expenditure. As per literature from various research results, the improvement of efficiency is the improvement of productivity. In addition, as per a definition given by the Cambridge dictionary; productivity is defined as the result of efficiency and effectiveness. As per the above definition, it can be inferred that efficiency affects the productivity of an institution.

According to the higher education proclamation, the first major objective is to prepare knowledgeable, skilled, and attitudinal mature graduates in numbers with a demand-based proportional balance of fields and disciplines so that the country shall become internationally competitive. Accordingly, this objective is used as one major indicator in evaluating the effectiveness of selected public universities for this study.

This research question aims to investigate the relationship between efficiency and productivity as well as to analyze the effect of efficiency on productivity. To achieve these objectives; average efficiency data and average total factor productivity change were used in pooled ordinary least square to regression in Stata 16.

The above model can be presented in the following equation as follows:

$$\text{TFPCH} = \beta0 + \beta1\text{eff} + \text{u}$$

4. RESULTS AND DISCUSSIONS

Table 1. Malmquist Index Summary of Annual Mean

Year	Efficiency Change	Technical Change	Pure Efficiency Change	Scale Efficiency Change	Total Factor Productivity Change
2015	0.976	0.815	1.01	0.967	0.796
2016	0.99	0.85	0.975	1.015	0.842
2017	1.084	0.998	1.057	1.026	1.082
2018	0.779	1.142	0.915	0.851	0.889
2019	1.127	1.106	1.03	1.094	1.246
2020	1.194	0.497	1.147	1.041	0.593
2021	0.795	1.002	0.844	0.943	0.797
2022	1.173	1.358	1.063	1.104	1.593
2023	1.039	0.844	0.976	1.065	0.877
Mean	1.007	0.926	0.998	1.009	0.932

Source: Researcher computation based on Malmquist productivity index (MPI) result, 2023

Based on the data presented in Table 1, a significant number of universities demonstrated improvements in efficiency and productivity during the study period from 2015 to 2023. Specifically, 56% of universities exhibited an improvement in efficiency change, while 45% showed an increase in technical efficiency change. Pure technical efficiency also saw a similar trend, with 56% of universities observing an improvement. Furthermore, 67% of universities experienced an increase in scale efficiency change.

Analysis of total factor productivity (TFP) change reveals considerable fluctuation. The highest TFP change was 1.593 in 2016, whereas the lowest was 0.593 in 2019. While TFP improved from 0.796 in 2010/11 to 0.877 in 2023, the mean TFP change across the entire study period shows a slight deterioration of 6.8% (0.932).

The productivity of the 22 universities over the period from 2015 to 2023 was not linear. Fluctuations were observed in total factor productivity change, as well as in technical change, pure efficiency change, and scale efficiency change. These efficiency changes are directly related to total factor productivity, as variations in these factors influence overall productivity.

Based on the data, the annual mean of total factor productivity (TFP) change shows a notable decline in 2015 to 0.796, which represents a 20.4% decrease in productivity. This decline was primarily driven by a decrease in technical change.

However, the following year saw a substantial rebound. In 2016, the average productivity increased by 34.6% relative to the 2015 score. Similar to the period from 2010 to 2011, the TFP change in 2017 was also significantly influenced by technical change.

In 2018, the productivity trend reversed, shifting from a decline to a positive growth of 1.082, a score greater than 1, primarily due to an overall improvement in efficiency. Despite this positive trend, TFP change then declined to 0.889, a drop attributed to a decrease in overall efficiency. However, it rebounded again in 2018, improving to 1.246 as a result of a change in inefficiency.

Overall, the annual mean TFP from 2015 to 2023 was generally on a declining trend, with the exception of 2023. Nevertheless, the annual mean productivity did improve from 0.796 to 0.932, even though the average productivity for the entire period remained below the threshold of one.

Factors Which Affect Productivity: Panel Data Analysis

Table 2. Summary of Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Tfpch	198	1.054	.651	0	5.013
Sech	198	1.046	.31	.418	2.866
Pech	198	1.053	.412	.249	4.009
Techch	198	1.015	.653	0	8.062

Source: Stata result based on MPI productivity result

As per the above summary of descriptive statistics table; the mean value of total factor productivity change is 1.054, which indicates that average productivity has increased by 5.4% at a 0.651 standard deviation. In addition, the maximum productivity is 5.013 and the minimum is zero. Similarly, the average change of scall efficiency change is 4.6%, the mean change of pure technical efficiency change is 5.3% and finally, the average change in technical change is about1.5%.

Coelli, (1994) decomposed MPI into pure efficiency change, scale change, and technological change under both CRS and VRS. The DEA-based MPI measures total factor productivity change can handle multiple inputs and outputs with minimal assumption and without information on input or output price. It can decompose productivity change into efficiency change (catch up effect) and technological change (frontier shift effect). It can help identify trends and patterns in the industry (technological change).

In above section 4.5; the total factor productivity study and the contributions of different types of efficiency to the total factor productivity change were discussed descriptively. In this section, this relationship will be tested using the panel data random effect model. To test the relationship, total factor productivity change (Tfpch) is considered as the dependent variable. The independent variables are efficiency types that contribute to the total factor productivity change which are technical efficiency change (Techch), pure efficiency change (Pech), and scale efficiency change (Sech).

To choose between the different panel models, Fixed effects are tested with a Fischer (F) test while random effects are explored with a Breusch and Pagan's Lagrange Multiplier (LM) test (Park, 2011).

According to Park (2011), the LM test contrasts the random effects with pooled OLS. As per Breusch and Pagan Lagrange multiplier test for random effects test result; the p-value in F-statistics shows Prob > chibar2 = 1.0000; which recommends the application of pooled rather than random effect**.**

Breusch and Pagan Lagrangian multiplier test for random effects

Estimated results	Variance	Standard deviation
Tfpch	.4236752	.6509034
E	.190219	.436141
U	.000	.000
Test: Var(u) = 0 chibar2(01) = 0.00 Prob > chibar2 = 1.000		

To decide which model to use among fixed effect and pooled OLS; Fixed effects are tested with a Fischer (F) was made. As per the fixed effect panel data regression result, the last column at the bottom of the table shows the p-value which exceeds 0.05. This indicates that the pooled ordinary least square model is recommended rather than a fixed-effect model.

Table 3: Fixed effect model Regression results

Tfpch	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Techch	.436	.049	8.87	0.00	.339	.534	***
Pech	.848	.081	10.52	0.00	.689	1.007	***
Sech	1.018	.104	9.77	0.00	.812	1.224	***
Constant	-1.346	.163	-8.25	0.00	-1.668	-1.024	***

Mean dependent var	1.054	SD dependent var	0.651
R-squared	0.587	Number of obs	198.000
F-test	81.866	Prob > F	0.000
Akaike crit. (AIC)	214.578	Bayesian crit. (BIC)	227.731

****** p<.01, ** p<.05, * p<.1***

Source: Stata 16 result, 2020

Variables definitions:
Tfpch - stands for total factor productivity change
Techch - stands for technical efficiency change
Pech - stands for pure efficiency change
Sech- stands for scale efficiency change

In the above table; the Stata 16 result shows that F statistics is 81.866 and Prob value is 0.0000. Since the P-value is less than 5%, it can be concluded that the model is adequate and analysis can be done about variables relationship and effects of the independent variable on dependent can be analyzed. As we can see in the above table R-squared 0.587. This indicates that more than 58% of total factor productivity change is explained by technological and efficiency changes included in this model.

In the above regression model result, the p- values of all the independent variables show PV less than 0.05. From this, it can be concluded that all independent variable technical efficiency change (Techch), pure efficiency change (Pech) and scale efficiency change (Sech) have a positive significant effect on the total factor productivity change (tfpch), since the p-value for all the three variables is significant at 0.05 level of significance.

Similarly, in the same table above; the coefficient values of all independent variables are positive. This also shows that all types of efficiency change have a positive contribution for total factor productivity change in Ethiopian public universities selected for the study.

The above findings explain that the increase in technical efficiency change (techch) by one unit increases total factor productivity change by .436, given that all other efficiency types are constant. Similarly; the change in pure technical efficiency (pech) by one unit increases the total factor productivity change by 0.847, keep other efficiency variables constant. In addition; the increase of scale efficiency change (sech) by one unit improves the total factor of productivity by 1.018, keep other efficiency types are constant.

In the above panel model; efficiency types, which are scale efficiency change and technical efficiency change have a significant contribution to the total productivity change as compared to pure efficiency change. One can conclude that productivity is mainly dependent on technological improvement and change in efficiency types like pure efficiency and scale efficiency changes.

It can be also recommended that universities' management and other concerned stakeholders need to work on the improvements of new technology and also management should work

to have an optimal size of the university in major operations to improve the productivity of universities since these variables have positive and significant effects.

This study result is consistent with Coili 1996. As per Coilli, technical change, pure technical efficiency change, and scale efficiency changes have a positive contribution to total factor productivity changes improvement. In addition; according to Fare et al. (1994b) total factor productivity growth is decomposed into the index of technological change and technical efficiency change. Index of has been further decomposed into pure technical efficiency change and scale efficiency change. Moreover, Fare et al. (1994b) concluded that all mentioned components are the contributors/ building blocks of total factor productivity. Darra (2006) in the study of Productivity Improvements in Education; a strategy for increasing productivity of higher education focuses on improving the two key components of productivity.

Table 4. Dynamic panel data model result

Tfpch	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
L.tfpch	-.13	.058	-2.24	.026	-.245	-.015	**

Techch	.417	.052	8.00	0	.314	.52	***
Pech	.839	.085	9.82	0	.67	1.008	***
Sech	1.019	.112	9.07	0	.797	1.241	***
Constant	-1.176	.193	-6.09	0	-1.558	-.795	***

Mean dependent var	1.084	SD dependent var	0.682
R-squared	0.601	Number of obs	176.000
F-test	56.406	Prob > F	0.000
Akaike crit. (AIC)	202.806	Bayesian crit. (BIC)	218.659

****** p<.01, ** p<.05, * p<.1***

In the above dynamic panel data model result, the r-square value is 0.601, which means the above identified productivity factors including lagged total factor productivity change explains almost 60% of the dependent variables, which is total factor productivity change. This result is almost same with static panel data model regressed using fixed effect panel data model, except for some improvement from 0.587 to 0.601.

As per the F-statistics result, the p-value is 0.000, which indicates that the model is fit and ready for interpretation of results. When we consider the significant level of each independent variable including the lagged efficiency, all have probability value less than 0.05; which have a similar level of significance with a static panel data model.

In addition to level of significance about independent variables; the sign of the coefficient for the independent variable is still positive except for the newly introduced lagged dependent variable (lagged efficiency). This is again in line with the fixed effect panel data model used in the static model.

According to the dynamic panel data model result, presented above technical efficiency change (techch), pure efficiency change (pech), and scale efficiency change have a positive and significant effect on total factor productivity change. In addition, it is also observed that the previous year's total factor productivity change has a positive effect on the current total factor productivity change. This result was also observed in the previous static panel data model. A small coefficient value decline was observed in the dynamic panel data model as compared to the static panel data model.

It can be concluded that even if the p-value results in the case of lagged dependent variable is significant and this also testifies the existence of an effect of the previous dependent variable on the current dependent variable (total factor productivity change); the above result ensures us that there is no result difference among the two-panel data model in this study. In addition, the similarity of the two-model results also gives the fitness of the model and the accuracy of the results.

Table 4. Hypothesis Testing result based on fixed effect model

Explanatory variables	Expected sign and effect on productivity change	Actual sign and effect on productivity change	Decision
Technical change	Positive and significant	Positive and significant	Accepted***
pure efficiency changes	Positive and significant	Positive and significant	Accepted***
scale efficiency changes	Positive and significant	Positive and significant	Accepted***

Accepted* stands for accepted at 1% level of significance**

Source: researcher formulation as per panel data regression results

Measuring the Relationship of Efficiency and Productivity

Efficiency is defined as doing the job well; moreover, productivity can be used for doing a useful job, which is a combination of both efficiency and effectiveness. As per this definition, productivity can be achieved only when a unit becomes efficient and effective. As per this concept; it can be inferred that there is a relationship between university efficiency with the productivity of universities.

To substantiate this concept; the relationship of change in technical efficiency and total factor productivity change is analyzed in this section. To test the effect of efficiency on total factor productivity change, the average efficiency result was taken as the independent variable and average total factor productivity change was considered as the dependent variable.

To study the relationship of efficiency and productivity of universities; pooled ordinary least square regression was applied. In the study, a change in efficiency score was considered as an independent variable, and universities' total factor productivity change determined by the Malmquist productivity index was also considered as a dependent variable. Nine years from 2015 to 2023 each university average efficiency change data and each university average total factor productivity change data were applied to assess the association and the effect of efficiency and productivity in the case of Ethiopian public universities categorized as first- and second-generation universities in Ethiopia.

Table 5: Summary of Descriptive Statistics of Efficiency and Productivity Changes

Variable	Obs	Mean	Std. Dev.	Max	Min
Efficiency	198	1.07916	. 4338823	3.246	0.332
Productivity	198	1.054495	.6509034	5.013	0

Source: Stata 16 result, 2023

According to the above summary of the change in efficiency and productivity table; the maximum efficiency change was 3.246 and the maximum productivity change was 5.013. In addition; the minimum efficiency change was 0.332 and similarly, the minimum total factor productivity change was 0. In the same table above; the mean of change in efficiency was 1.07916 and the mean of change in productivity was 1.054495 with a standard deviation of 0.4338823 and 0. 6509034 respectively. As per the above summary of the change in efficiency and productivity table; nine years of data from twenty-two universities average efficiency score is 1.07916. This means the average maximum efficiency is 7.916% (1.07916-1) *100 and the average maximum productivity improvement is around 5.5% (1.054495-.1) *100 in the selected universities.

Table 6: Fixed effect results on the effect of efficiency change on change in productivity

Tfpch	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Effch	1.054	.08	13.13	.0000	.896	1.213	***
Constant	-.083	.093	-0.89	.3730	-.267	.101	
Mean dependent var	1.054		SD dependent var		0.651		
R-squared	0.496		Number of obs		198.000		
F-test	172.317		Prob > F		0.000		
Akaike crit. (AIC)	249.814		Bayesian crit. (BIC)		256.391		

****** p<.01, ** p<.05, * p<.1***

Source: Stata 16 result, 2023

To test the effect of technical efficiency over productivity; a fixed effect panel data model was used to generate the following regression result. To correct the heteroscedasticity problem, a robust result of panel data fixed effect regression was used for the analysis.

As per the result, F statistics shows that the p-value is .0000, which means the model is significant at a .05 level of significance, and also the model fits for analysis. The r square result shows how the dependent variable, in this case, change in total factor productivity (tfpch) is explained by the independent variable; the change in efficiency (effch). As per the model result, the r-square is 49.6%, which means the change in efficiency affects the change in the total factor productivity by 49.6%. These shows there are still other variables that affect the change in the productivity of public universities.

To analyze the independent variable affects the dependent variable uniquely; the P-value should be significant. According to the regression result; the P-value of an independent variable, efficiency change is .000, which is significant at 0.05 levels. This indicated that change inefficiency affects the total factor productivity change uniquely. In the model; the coefficient of change in efficiency is 1.054. Since the coefficient is positive. It shows that a positive relationship exists between change in efficiency and change in total factor productivity. Regarding the value of the coefficient of the change in efficiency, it indicates the significance of the independent variable on a dependent variable. This is also showing that the change in total factor productivity increases by 1.054 when the change in efficiency increases by one unit.

This finding is consistent with a study made by C Barra and Zotti (2013) and C Barra and Zotti (2013). In their study on a relationship between productivity and efficiency; they concluded that productivity is the efficiency of transforming inputs to outputs. In addition; this finding is also supported by a study on decision making and Productivity Measurement by Dariush (2018). He concluded that productivity is the result of efficient and effective business results. Hibbert et al. (2013) also mentioned that efficient utilization of resources brings better productivity in a firm. Similarly, Henri (2004) concluded that if a firm takes up steps to consume resources efficiently, the firm's productivity will be improved easily.

Summary of Hypothesis Testing

Ho4: There is no relationship between expenditure efficiency and productivity of public universities

H_a4: There is a strong relationship between expenditure efficiency and productivity of public universities

According to the fixed effect model result, the p-value for the efficiency change variable (effch) is 0.000. This result recommends rejecting the null hypothesis and accepting the alternative, meaning that there is a strong relationship between expenditure efficiency and productivity of public universities. In addition; efficiency change affects change in productivity positively.

5. CONCLUSION

This study's main objective was to evaluate the productivity of education expenditure and identify the factors influencing Total Factor Productivity (TFP) change in selected public universities. Using a 9-year panel data set, the dependent variable, TFP, was measured with the Malmquist productivity index. The major findings from the random effect panel data model indicate that all three independent variables—technical efficiency change, pure technical efficiency change, and scale efficiency change—have a statistically significant positive effect on TFP change. Specifically, an increase of one unit in technical efficiency change boosts TFP change by 0.436, while a one-unit increase in pure technical efficiency change leads to a 0.847 increase in TFP change. The study also found that a one-unit increase in scale efficiency change improves TFP change by 1.018. In conclusion, the results confirm that improvements in all three efficiency types are crucial for enhancing the overall total factor productivity of educational expenditure. In addition; efficiency has positive and significant effect on productivity.

6. DECLARATION

We, the authors, declare that this article is our original work, written in its entirety by the three of us. All sources of information used in this article have been properly cited and acknowledged. This article has not been submitted for publication in any other journal.

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