Human Capital in the Sub Saharan African Countries: Productivity and the Policy Implications

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Abstract: This paper investigates the contribution of higher education human capital to productivity in Sub-Saharan African (SSA) countries by measuring higher education human capital in two variables: higher education enrolment (HEE) and higher education graduations (HEG). The paper analysesa panel data of 30 SSAcountries for the period 1980 -2015 using, a fixed effect Least Square Dummy Variable (LSDV) model, and a System Generalized Methods of Moments (GMM) modelto verify empirically the claim that higher education human capital improves productivity in SSA. It is found that the impact of higher education (both HEE and HEG) on total factor productivity (TFP) in sub-Saharan Africa is mixed as it is positive for HEE and negative for HEG. The results on the impact of HEG suggest that higher education sector suffers from inadequate human capital that might not be put to use for productive purposes. These results imply that the higher education in SSA needs to target skills that are more appropriate to the economies in these countries.

Keywords: Human Capital; Productivity; Sub Saharan Africa; Higher Education Enrolment. Higher education graduations

JEL Classification: J24; I23; O49

1. Introduction

Between 1980 and 2000, sub-Saharan African (SSA) countries witnessed low economic growth, low productivity and low higher education enrolment (HEE) (Glewwe, Maiga & Zheng, 2014). The SSA region covers a large portion (22 million sq. km) of the African continent. It is larger than China (9.3 million square km), India (2.97 square km) and the United States of America (USA) (9.1 square km) and it is five times bigger than the 28 nations in the European Union (CIA 2017, World Map, 2017). The SSA population is estimated at more than 930

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million, twice that of the European Union. While this population profile should give the SSA region a competitive edge, the evidence of low productivity is a cause of concern (Bloom, Canning, Chan & Luca, 2014). With human capital being crucialin the production processes, policies to increase productivity in SSA can be informed by the evidence on theeffects ofhigher education human capital on productivity in this region (Olamosu & Andy, 2015).

Evidence in SSA suggests that poor human capital formation and low productivity levels area result of little progress made in raising the levels of education in general and the levels of higher education in particular (Glewwe et al., 2014). These low levels might have in turn been detrimental to the formation of higher education human capital. Given the role higher education human capital is expected to play in productivity enhancement, it follows that the SSA region is unlikely to compete globally in innovation, technology and productivity unless higher education policies are reviewed to enhance the effects of education on productivity (Adewunmi, 2011). In spite of the need for policies on higher education to make it more relevant to productivity needs of the region, there has not been sufficient investigation to this effect.

Based on this background, there is a need to examine the role higher education human capital plays on productivity in the region, specifically the role of HEE and HEG. The claim put forward in this paper is that HEE and HEG increase productivity in SSA. However, subjecting this claim to empirical investigations, it turns out to be supported partly by the evidence, pointing out to a need to review higher education policies in this region

This paper is organized as follows: the next section discusses the literature, section 3 presents the methodology employed, section 4 presents the results and concludes the study.

2. Literature Review

2.1. Theoretical Foundation

The main argument in this paper is that higher education human capital (HEE and HEG) is expected to contribute to productivity in SSA. This expectation arises from the fact that higher education equips people with required skills in order to be more productive and to use other factors of production more efficiently. The investigation around this argument in SSA is however necessary because there has been mixed evidence around theoretical predictions in line with this logic.

The main theory predicating the role of higher education (HEE and HEG) on productivity is the human capital theory. Human capital theory originates from the 1950s' difficulties in explaining productivity and economic growth in the US

Economy. In his seminal work on human capital theory, Becker (1962) challenged the conventional understanding at the time that physical capital was the predominant factor behind growth in productivity in the US economy. Becker (1962) contended that human capital was instead the main factor explaining growth in productivity at the time.

In essence Becker (1962)'s theory explains that human capital, through education, enhances productivity. One of the implied theoretical foundations of Becker (1962)' theory is the role human capital plays in total factor productivity (TFP). Defined as the additional output in an economy that cannot be explained by employed factors of productions, TFP is explained indirectly by many human capital and growth theories. The common formulations of these theories is that human capital plays a principal role not only in increasing the productivity of labour itself but also the productivity of other factors of productions. In this perspective, Becker (1962) explains this role by acknowledging that, the extent to which individuals learn new skills and perfect old ones for productive purposes depends on human capital which enhances productivity of labour and other factors of production. Furthermore, De la Fuente (2002) states that models of human capital and productivity are built on the hypothesis that the knowledge and skills embodied in human capital directly raise productivity and increase an economy's ability to develop and adopt new technologies

Consistent with the prediction of Becker (1962), Mankiw et al. (1990) evaluated the predictions of Sollow (1956) 'sgrowth model andindicated that human capital omission in the model was the underlying reaons for its unrealistic predictions. Solow(1965) growth modelshad put forward the capital accumulation, labour, population grwoth and producitivtyy as factos explaining growth. The model had explained that the level of savings and pupulation growth determined the level of producitivty and income per capita. Specifically higher popualtion growth reduced producvity/ income per capita and higher levels of savings increaased producivitiy/ aincome per capita. In essence, the model's predictions were correct in terms of the directionsof the effectspopulation growoth and savings on income per capitabut not on the maginitues. In other words, one would find countries with comparable increase in population growth, other things remaining the same, having different levels of reduction in income per capita (different steady states). Augmenting the model by inclusion of human capital, Mankiw (1990) modelbrought aboutpredictions that were closerto word realities. This enahancedthe understanding of the role human capital plays enhacingin productivity.

Other theories and models focused on the mechanisms through which human capital contribute to productivity. One of the models in this line of thinking was Lucas (1988), who postulated that when human capital is put to use, a fraction of it contributes directly to productivity of labour whilst another contributes to the accumulation of future human capital. Similarly, Mankiw, Romer and Weil (1992) observed that the accumulation of human capital could increase the productivity of other factors and thereby raise productivity growth.

In these models education has been the main channel through which efficient use of labour and other factors could lead to higher productivity. In this perspective, the signalling theory of Spencer (1973) is worth noting. This theory explains that the higher the person is educated, the lower the cost of acquiring education. According to the theory, the easiness of accumulating educational skills signals also the ability with which the person acquires job level skills, and commits to innovation and technology. Other literature's realisation that a more educated labour force innovate at a faster rate (Spiegel, 1994; Chevalier, Harmon, Walker & Zhu, 2004; Chevalier, Harmon, Walker & Zhu, 2004) support the insinuationsof theoretical models that that individuals with higher education are more productive.

In summary, human capital theoretical models are premised on the postulation that the embodiment of skills and knowledge acquisition in human capital directly raises productivity, lead to the adoption of new technologies, and results in improved productivity and economic performance. The empirical analyses on these theoretical predictions have however resulted in mixed evidence.[1] In particular the evidence in SSA has not been consistent with theoretical models (De la Fuente, 2002).The results reported in some studies have led scholars to question the functional role played by education in the productivity processes. Some of their findings are highlighted in the next section.

2.2. Empirical Studies

Empirical analyses related to this paper consist of studies that evaluated the effect of human capital on productivity or on economic growth. These studies can be classified according to their thematic focus and geographic coverage. One of the studies that covered broad geographical areas was a study by Miller & Updadyay (2002). In this study, TFP was evaluated by grouping countries according to different levels of development. The focus was to assess whether the level openness and human capital accumulation promote productivity of the factors of production and economic growth (Miller & Upadhyay, 2002) Using the Cob-Douglas production function specifications for a 30-year panel for 83 countries representing all regions of the world and all income groups, the study compared labour and capital elasticity of output per worker across each of several income and geographic groups, finding significant differences in TFP across countries, income and regional groups. Assessing the determinants of TFP that included, among many others, human capital, openness, and distortion of domestic prices relative to world prices, the study concluded that, a policy of outward orientation may or may

[1] See (Pritchett, 2001; Gyimah-Brempong et al., 2006 for instance).

not promote growth in specific country groups, even if geared to reduce price distortion and increase openness. The study further concluded that human capital plays a smaller role in enhancing growth through TFP.

A similar study covering developed and developing countries focused on evaluating the extent of the effect technology and other effects on TFP. Using a two -step approach, the study estimated TFP arising from education and health using the Cobb-Douglas production function in the first step; and analyzed the determinants of TFP by paying special attention to indicators of health, in the second step. The panel data used in the analysis covered the period 1990-210 for 37 developed and developing economies. Life expectancy and average years of schooling were used as health and education indicators, respectively. The fixed and random effects approaches were adopted as the estimating technique. The outcome of the research suggested that both health and education had a positive, significant and robust impact on TFP. The evidence highlighted the importance of improving health and education through policy implementation so as to ensure long-run sustainable economic growth. Likewise, a study by Baier, Dwyer, and Tamura (2006), spanning 145 countries across the world, used the growth accounting framework to compare the growth in output per worker and growth in physical and human capital. Assuming a constant return to scale, the study estimated the implied growth of output per worker from the growth of physical and human capital. Furthermore, in order to understand, the effects of physical and human capital on unexplained growth, the study estimated the difference between the output growth implied by a constant return to scale and the actual growth in output (the difference being TFP) The findings were that the weighted average TFP from human capital and physical capital accounted only for 14% of the growth in output per worker with the rest (8%) being explained by the productivity of these factors of production. Reporting these findings by region, the study found that TFP contributed to growth of output per worker by 34% in Western countries, 26% in Southern Europe and 26% in newly industrialized countries. In contrast, for countries in SSA and in East Asia, TPF contributed negatively to growth of output per worker, suggesting that more than just technology explained the growth of TFP in these countries.

In the Organization for Economic Cooperation and Development (OECD) countries, De la Feunte (2011) examined the effects of human capital on productivity among some OECD countries. Using average years of schooling as a proxy for human capital and biennial data in the period 1965-1995 as well as linking the Cobb-Douglas production function to the technical progress function, the paper found that human capital had a large and positive coefficient value. The coefficient for Spain was higher than that of other OECD countries under investigation. The productivity share of human capital for Spain accounted for a 40% productivity gap and 30% for other OECD countries

In SSA, Omitogun, Osoba and Tella (2016) examined the interactive impacts of the nexus between human capital investment components and economic growth in Nigeria for the period of 1986-2014. The study indicated that although much of the research work had focused on the relationship between economic growth and human capital across the globe, there was a gap in knowledge on the joint influence of human capital investment components on economic growth, especially in Nigeria. The study further engaged secondary annual data on education expenditure; real gross domestic product; health expenditure; and gross capital formation extracted from the Central Bank Statistical bulletin. Using a Fully Modified Ordinary Least Squares (FMOLS) technique, the study found that that that there was a significant and positive relationship between the interactive impacts of human capital components and growth in Nigeria. The second study conducted in Nigeria was by Babasanya, Oseni and Subair (2018) who examined the effects of human capital development on poverty alleviation in Nigeria over the last twenty seven years (1990-2017). The findings from the outcome of the result obtained was expected to help foresee the possibility of investment expenditure in human capital to maximize the prospects of achieving Sustainable Development Goals (SDGs) objectives by 2030. From the standard Cobb-Douglas production function and Solow's neo-classical growth theory, the study adopted a log-linear regression model that was sequentially formulated. The prevailing effects of poverty rate as a percentage of total population was regressed on real government expenditures, health, education as well as the unemployment rate. The outcome of the estimated model indicated that real government expenditure, unemployment rate education had all significantly impacts on the prevalence of poverty in Nigeria. The third study conducted in Nigeria was byNachega and Fontaine (2006) who examined the factors that determine growth in TFP between 1963 and 2003. The emphasis in this research was the investigation of economic trend of event and their empirical implications on output with special interest on the sources of growth in aggregate outputs and the TFP determinants. Adapting the growth accounting framework to the Cobb-Douglass model, the analysis showed that the decrease in output per capita over the sample period was caused by negative TFP growth for physical capital per capita. Sound macroeconomic policies, supported by official development assistance and structural reforms, were found to be the key to raising TFP growth.

The above-reviewed literature suggests that there has not been sufficient studies evaluating the role of human capital on productivity in SSA as block. So this study contribute to the literature in twofold. First none of the studies conducted focused on the productivity of higher education human capital. Most studies have to date been focusing on the role of human capital on economic growth or on poverty and these studies have been mainly on one country in SSA. The other study we are aware of notably Glewwe et al, (2014) evaluated the role of education on productivity more generally. The only study that was closely related to one reported in this paper was a study by Agree, Eliab & Joseph, (2010). While this study investigated the effect of human capital on labour productivity in SSA, it focused analysis at a firm level by investigating producutity of human capital across manufacturing firms in only three of the 46 countries in the SSA region notably Uganda, Kenya and Tanzania. While the evidence was that skilled workers and more educated worker had had the most significant impact on manufacturing productivity in these countries, these evidence cannot apply to the effect of higher education human capital on productivity. Second, none of the studies distinguished, as this paper does, the effects on productivity from the higher education enrolment point of view and graduations point of view.

3. Methodology

3.1. Model Specification

As is the case in the literature, the Cobb-Douglas production function is the model adopted to investigate the role of higher education human capital on productivity. The study follows closely the De la Feunte (2011) and Pritchett (2001). The central concern in this paper is to view human capital from the perspective of HEE and HEG, and how these independent variables affect the growth of the economy via TFP.

Taking the augmented type of Cobb-Douglas production function from Fuente (2011) in which:

$$Y_{it} = A_{it}\, K_{it}^{\alpha k} H_{it}^{\alpha h} L_{it}^{\alpha l} \qquad (3.1)$$

Where Y_{it} = Total output in a given country i at time t.

L_{it} = Employment level, K_{it}= Physical stock. H_{it} is the stock of human capital, and is disaggregated such that $H_{it}= (HEE_{it}+HEG_{it})$. HEE is enrolment in higher education and HEG is higher education graduates. Elasticity with respect to the stock of the various factors is measured through the coefficient α_i (with $I = k,h,l$).

First, we define productivity as follows: Per capita production function relates average labour productivity to average schooling and to the stock of capital per worker such that outputs per worker = $Q=Y/L$, and stock of capital per worker=$Z=K/L$, stock of human capital per worker= $W= H/L$ by dividing equation (3.1) .1 through by total employment L yields:

$$Q_{it}= AZ_{it}^{\alpha z}\, W_{it}^{\alpha w} \qquad (3.2)$$

To provide for TFP, the new Cobb-Douglas function is in the form:

$$Y_{it} = A_{it}\, K_{it}^{\alpha k}\, HEE_{it}^{\alpha hee} HEG^{\alpha heg} L_{it}^{\alpha l} \qquad (3.3)$$

With constant return to scale (*αk+αhee+αheg+αl =1*), linear equation level is produced by taking the logs and we can assume a growth rate of *y= dln (Y/L) dt,* which relates the annual percentage growth of output per worker to the growth of physical capital per worker and educational capital per worker. We introduce $\mu_{it,}$ to capture the unexplained phenomenon (random shock) which was not captured in the adjustment process.

This leads to:

$$Y_{it} = a_{it} + \alpha k(k_{it}) + \alpha hee(HEE)_{it} + \alpha heg(HEG)_{it} - \mu_{it} \qquad (3.4)$$

Since a_{it} is the accounting residual growth known as TFP.

$$A_{it} = Y_{it} - \alpha k(K_{it}) - \alpha hee(HEE_{it}) - \alpha heg(HEG_{it}) - \mu_{it} \qquad (3.5)$$

In order to build a dynamic model into the system for TFP, we introduce the lag of dependent variable to the right-hand side:

$$A_{it} = Y_{it} - A_{it-1} - \alpha k(K_{it}) - \alpha hee(HEE_{it}) - \alpha heg(HEG_{it}) - \mu_{it} \qquad (3.6)$$

3.2. Estimating Technique

Basically, models in panel data can be put in two categories: The first is the static panel model and the other is the dynamics panel model (Bai, 2009). The two static panel models identified in the literature are the within group panel fixed effect and the least square dummy variable (LSDV) which is an extension of fixed effect and random effects (Rowland & Torres, 2004).

The use of fixed effect has been largely supported in the literature because of its ability to produce a consistent estimator (Blundell, Bond & Windmeijer, 2001). GMM)

To account for the dynamic nature of our model and in order to control for the endogeneity problem, GMM is adopted in the method of estimation. Dynamic panel models have been identified as a technique to improve the performance of the estimators in panel data analysis. This approach was popularized by Arellano and Bond (1991). According to Oyedokun, Folly, and Chowdhury (2009), when a static specification of the fixed effects model is joined with autoregressive coefficients, which is the lagged value of the dependent variable, it allows feedback from past or current shocks to the current value of the dependent variable. This method of specification is known as GMM. The dynamic specification removes the temporal autocorrelation in the residuals and prevents a spurious regression being run, which may lead to inconsistent estimators. The GMM model that describes the relationship among education enrolment, education graduates and productivity in SSA countries is specified as follows

$$a_{it} = \beta_{it} + \rho a_{it-1} - \beta_2 k_{2it} - \beta_3 hee_{3it} - \beta_4 heo_{4it} - \mu_{it} \qquad (3.7)$$

Equation (4.11) is the modified form of the representation of equation (4.10) in dynamic panel data form with the addition of the lagged value of the dependent variable. Consequently, by taking the first difference of equation (4.11), we obtain equation (4.12) as follows:

$$\Delta a_{it} = \beta_1 + \rho\Delta a_{it-1} - \beta_2\Delta k_{2it} - \beta_3\Delta hee_{3it} - \beta_4\Delta hee_{4it} - \Delta\psi_{it} \qquad (3.8)$$

In order to avoid possible correlation between a_{it-1} and ψ_{it}, an instrumental variable Z' that will not be correlated with both is obtained through matrix transposition of the explanatory variable. Equation (4.12) is multiplied in vector form by Z' leading to:

$$Z\Delta y_{it} \; Z'\Delta a_{it} = \beta_1 + Z'(\Delta a_{it-1})\rho - Z'(x_{it})\beta - Z'\Delta\psi_{it} \qquad (3.9)$$

Estimating equation (3.9) using the generalized least square (GLS) yields one-step consistent GMM estimators. However, the additional input to the approach used by Arellano and Bond (1991) evolved over the years and was developed by Blundell et al. (2001). It is referred to as system-GMM (SYS-GMM). The difference between this approach and GMM is that SYS-GMM exercises more precaution in the usage of the instrumental variables. It was developed to tackle the problem of possible weak instrumental variables, which may occur in GMM. Therefore, SYS-GMM is expected to yield more consistent and efficient parameter estimates, especially in the event of larger time periods; hence, the preference for SYS-GMM in this paper.

3.3. Data and Variables

This paper adopts panel data for 30 countries for the period 1981-2015 to estimate the paper's models. The paper first estimated the Cobb-Douglas production function in order to achieve the objectives of the paper. The variables and data for production function are real GDP per worker, higher education (both enrolment and graduates), real capital stock per worker and labor force.

Real output per worker: The conventional dependent variable in the Cobb-Douglas production function is the real output per worker. The paper applied real GDP in US dollars at constant prices (2000) by adopting Penn World Table 9.0 data from 1980-2015. It is divided by labour force to obtain real output per worker.

Capital enters the production process with labour to produce units of output. It is the tangible object that aids better performance of productive activity. In the Cobb-Douglas production function, capital stock per worker is an independent variable. The capital stock data is readily available for most of the countries in the SSA region, to calculate the capital stock for the time-period covering 1980-2015.

In the context of this paper, TFP is the dependent variable. TFP is of great importance in accounting for economic growth, economic fluctuations and differences in cross-country per capita income. When considering frequencies in the business cycle, TFP always correlates with output and hours worked. In the new growth theory, human capital levels affect productivity growth. Productivity growth measurement is required to trace technical change in an economy. We follow literature to measure TFP as the residual of labour and capital in the Cob Douglas model.

HEE and HEG are two independent variables that proxy human capital. In the context of this paper, it is believed that HEE is an important determinant of human capital, and while not all that enroll for higher education eventually graduate, the process of human capital has begun. The paper aimed to establish if the two human capital variables independently impact on TFP. This is because the differences in the macro-economic variables could possibly account for the dropout rates higher education among the countries under investigation.

3.4. Data Sources

The data for HEG and HEE are available in Baro and Lee's (1950-2010) data sets for the period 1980-2010 while the data to cover the period 2015 are available in the new version of Baro and Lee's (2015-2040) data sets. The two columns referred to as "tertiary total" and "tertiary completed" under tertiary in Baro and Lee's data sets are referred to as HEE and HEG, respectively, in this paper. Data on real GDP, capital stock, and employment rates are adopted from the Penn World Table 9.0 for 1980-2015. The paper adopts a similar approach to data selection as that developed by Tang et al. (2008). Data from the Penn World Tables are annual data while those from the Barro and Lee dataset (1950-2010 and 2015-2040) are in five-year averages. To gain the degree of freedom required for the data, data on HEE and HEG from the Barro and Lee dataset were interpolated from e-view 9.5.

4. Empirical Analysis

4.1. Pre-Estimation Test

4.1.1. The Panel Unit Root Results

The presence of unit roots in economic models has theoretical implications, which often leads to spurious regression analysis. This research followed that of other researchers to determine the true nature of the variables. We check for the presence of unit roots because certain variables tend to exhibit certain characteristics such as finite variance and mean reversion. This paper therefore tested for the stationarity (unit roots) of variables using a robust version of Levin, Lin and Chu (LLC), Im, Pesaran and Shin (IPS) and Augmented Dickey-Fuller Test (ADF) at the individual intercept. Various approaches were adopted for the test to ensure consistency and in order to compare and validate the results (Moon, Perron, & Phillips, 2007). The results confirmed that all the variables were non-stationary at I (0), except TFP which when converted, were all made stationary after first differencing. The results are shown in the table 1 below. All the P-values are shown at 1% level of significance.

Table 1. Levin, Lin and Shu, Im Pesaran & and ADF-Fisher Chi-square Panel Unit Root Results

Variables	Levin, Lin and Shu		Im Pesaran & Shin		ADF- Fisher Chi- square	
	P-value	Order of Integration	P-value	Order of Integration	P-value	Order of Integration
LOGCK	0.0310	I(1)	0.0048	I(1)	0.0114	I(1)
TFP	0.0016	I(0)	0.0805	I(0)	0.0025	I(0)
EMR	0.1079	I(1)	0.0000	I(1)	0.0000	I(1)
HEE	0.0000	I(1)	0.0000	I(1)	0.0000	I(1)
HEG	0.0000	I(1)	0.0000	I(1)	0.0000	I(1)
LogRGDPNA	0,0000	I(1)	0,0000	I(1)	0.0000	I(1)

Source: Author's Computation, 2018

4.1.2. Summary Descriptive Statistics

The summary statistics of pooled observations for this paper are presented in this section for all the variables adopted in the analysis that showcase the impacts of HEE and its graduates on TFP among the SSA countries under investigation. The descriptive characteristics operate around the maximum and minimum values, its mean, standard deviation and median across variables in the panel data.

Table 2. Summary Descriptive Statistics

Variables	TFP	Y/L	HEG	HEE	C/L
Mean	1.85E-09	9.024	0.030	0.056	9.522
Median	-0.031	3.569	0.014	0.026	3.824
Maximum	1.535	67.381	1.330	2.600	66.131
Minimum	-2.089	0.453	-0.980	-1.570	0.464
Std. Dev.	0.498	11.297	0.099	0.198	11.777
Skewness	0.212	2.017	3.265	3.969	1.942
Kurtosis	3.867	7.336	57.927	50.433	6.845
Jarque-Bera	41.892	1578.172	137682.8	104078.9	1344.159
Probability	0.000	0.000	0.000	0.000	0.000
Sum	2.00E-06	9745.841	31.945	60.715	10283.47
Sum Sq. Dev.	268.108	137708.0	10.497	42.434	149644.3
Observations	1080	1080	1080	1080	1080

Source: Author's Computation, 2018

The series displayed in Table 2 above exhibits generally low values as all the results tend towards the minimum rather than the maximum. Again, the standard deviation and mean values consistently fall within the minimum rather than the maximum range in the series. The standard deviations in most parts of the series exhibit relatively low values, which shows that deviation of only small amount of the actual data is obtained from their mean values.

Specifically, in the case of TFP which is the dependent variable, we found that its maximum value is 1.534578 whereas the minimum is as low as -2.088724 with a mean of 1.85E-09 which is closer to the minimum than the maximum. The claim is strongly confirmed by standard deviation since it is closer to the mean. This result substantially supports extant a priori expectations that TFP is low in the SSA region. While the value is generally low, it indicates that TFP would grow given policy implementation in the right direction.

Again, it is noted that the result for HEG, HEE, capital per labour (C/L) and output per labour (Y/L) follow a similar trend as the TFP with their mean also closer to the minimum. For instance, the mean value for HEG is 0.029579 which is closer to the minimum of -0.98 whereas the maximum value is 1.33. A quick look at the comparative value of its standard deviation (0.098631) indicates that it is not too far from the mean. For all the results, the relatively low value of the standard deviations for most of the series shows that there is only a small amount of deviation in the actual data from their mean value. Hence in relative terms, all these variables are fundamentally low in their contributions to TFP.

4.1.3. Correlation Matrix Analysis

To ascertain that the problem of multi-collinearity does not exist in the paper's estimations, this section presents the degree of association among the variables.

Table 3. Correlation Matrix Analysis

Variables	TFP	Y/L	HEG	HEE	C/L
TFP	1.000	0.072	0.018	0.040	0.025
Y/L	0.072	1.000	0.056	0.040	0.997
HEG	0.018	0.057	1.000	0.947	0.051
HEE	0.040	0.040	0.947	1.000	0.035
C/L	0.025	0.997	0.051	0.035	1.000

Source: Author's Computation, 2018

Table 3 above showcases the correlation matrix which indicates the correlation structure among the variables adopted in this panel model. The variables exhibit various forms of association with one another. However, the paper pays special attention to existing associations between TFP and Y/L, HEG, HEE, C/L which are the explanatory variables as these are the main focus of our paper.

Generally, the pairs of variables are all positively correlated, meaning that as the level of TFP increases, the corresponding independent variables increase. Strong correlation exceeding 0.9967 is only apparent in three variables, while all the other variables exhibit significantly weak associations. There is a weak association between *CL*, *YL*, HEE, HEG and TFP. The results appear to corroborate those obtained in the summary of statistics in Table 2. This is an interesting result as it indicates that the variables in our estimation do not suffer from the problem of multi-collinearity.

Having completed the descriptive and correlation analysis, the econometric analysis is done to either confirm or refute the sketchy conclusions made under the descriptive analysis. Consequently, the paper progresses to panel data analyses which begin with fixed effects least squares dummy variable (LSDV) and the findings are as shown in Table 4 below.

Using panel data analysis is justified in that it takes care of unobserved heterogeneity. In order to explain the cause-effect relationship between the dependent and the independent variables in detail and to show the within variations, the paper adopted the ordinary least square, fixed effect and random effects and Hausman test estimating techniques in the model.The Hausman test is required for the selection of the most appropriate model. Based on the nature of the data and the results of the Hausman test, the paper reports the results from fixed effects (within) regression where we have 35 time series and five cross-sectional variables. As shown in the methodology, the paper adopts only the fixed effects analysis. This is explored in the form of within variation and LSDV.

Table 4. Ordinary Least Square regression

TFP	Coefficient	Corrected std. Error	Z	P>|z|
CL	-0.303	.0128752	-23.56	0.000
YL	0.319	.013426	23.72	0.000
HEE	0.610	.192824	3.17	0.002
HEG	-1.289	.3881349	-3.32	0.001
Cons	0.017	.0161608	1.08	0.279

Source: Author's Computation, 2018

R square = 0,3477; Adjusted R-square = 0,3453; Prob>F = 0.0000; F(4,1075) = 143.24

4.1.4. Random Effects (within variation regression) Estimation Results

This section reports on the results from random effects regression among the series: *TFP* as the outcome variable; *CL, YL*, *HEE* and *HEG*.

Table 5. Random Effects (within variation regression) Estimation Results

TFP	Coeff	Correc standard.Error	Z	P>|z|
CL	-0.283	0.012	-22.90	0.000
YL	0.279	0.011	24.61	0.000
HEE	0.458	0.118	3.87	0.000
HEG	-0.954	0.238	-4.00	0.000
CONS	0.180	0.065	2.77	0.000

Source: Author's Computation, 2018

R square = 0.4011; R.sq: within = 0.1326; Adjusted R-square = 0,345; Prob>F = 0.000

4.1.5. Fixed Effects (within variation regression) Estimation Results

The results from fixed effects regression among the series are reported in this section: *TFP* as the outcome variable; *CL*, *YL*, *HEE* and *HEG.*

Table 6. Fixed Effects (within variation regression) Estimation Results.

TFP	Coefficient	Corrected standard Error	Z	P>|z|
CL	-.3002846	0.013	-22.72	0.000
YL	.2914905	0.012	24.59	0.000
HEE	0.450	0.117	3.84	0.000
HEG	-0.939	0.237	-3.97	0.000
CONS	0.231	0.028	8.16	0.000

Source: Author's Computation, 2018

R.sq: within = 0.4030; F(4,1046) = 176.53; R.sq: within = 0.4030; Adjusted R-square = 0,3453

Prob>F = 0.0000

4.1.6. Hausman Test Regression

This section reports the results from the Hausman test conducted to ascertain the more appropriate model between fixed and random effects.

Table 7. Hausman Test Regression

Variables	b (fe)	B (re)	(b-B) difference	Sqrt (diag(V_b-V_B)) S.E.
CL	-0.300	-0.283	-0.017	0.005
YL	0.291	0.279	0.012	0.003
HEE	0.450	0.458	-0.007	-
HEG	-0.939	-0.954	0.015	-

Source: Author's Computation, 2018

Chi2(4) = (b-B)'[(V_b-V_B)^(-1)](b-B) =11.98, Prob>chi2 = 0.0175

Tables 5 and 6 present the outcome of our findings in the panel model under investigation. The paper reported the results from both the fixed and random effects. It further investigated through the Hausman test the most appropriate model and the result shows that there is remarkable difference between the two models. From the paper's hypothesis testing:

Ho = Random effects model is the appropriate model to be adopted.

Ha = Fixed effects model is the appropriate model to be adopted.

The result of Hausman test indicates that we do not accept the null hypothesis (Ho); we reject the null hypothesis and accept the alternative hypothesis, and hence, we accept the fixed effects model as the appropriate model. The adoption of this model is premised on the fact that it can handle the heterogeneity effect that may influence the outcome of our findings. In a fixed effects model, all the variables, namely, capital stock per worker, output per worker, HEE and its graduates are statistically significant. Again, output per worker and HEE are all positively signed in the models while capital per worker and HEG are negatively signed. The outcome of this result suggests the nature of the relationship (that is direct or inverse) between each of the significant variables and TFP. Hence the first step towards understanding the nature of relationship between the explanatory variables and the TFP has been achieved. As indicated by the results, there is a high expectation that the human capital variables employed in this paper are likely to contribute to TFP growth among the SSA countries under investigation. However, to establish their individual effects, the dynamic panel model is important.

The R-square is below average in the model. This is because all the explanatory variables account for an average of 40% variation in TFP growth among the SSA countries under investigation. The model is tested for overall significance to corroborate the R-square results through the F-test for fixed effect The F value of 176.53 is significantly different from zero at 1% level of confidence.

The results indicate that the model passed the overall significance test. The results thus far also indicate that the choice of the variables adopted in this paper appears to be appropriate.

In addition, from Table 7, it is obvious that there is an inverse relationship between TFP per capita per worker. In a sense, this result supports the evidence from the capital utilization theory, showing that there is underutilization of capital among the countries under investigation because the inverse relationship can be assumed for a situation where capital per worker in the economy is relatively low thereby inhibiting the growth of TFP. The coefficient is statistically significant. Again, one of the two important variables in this model is HEG which also exhibits an inverse relationship with TFP. An increase in HEG leads to decrease in TFP, because as the SSA countries under investigation produce more graduates, they are not put to productive use in the economy.

The empirical literature also indicates the possible tendency of cross-sectional dependence in panel results, and this requires an analysis of the significant differences in the SSA countries' intercepts test by adopting the fixed effect LSDV shown below.

Table 7. Fixed Effects (LSDV) Estimation

The results from fixed effects (LSDV) regression are reported in this section among the series: TFP as the outcome variable; *C/L, Y/L*, HEE and HEG.

Table 8. Fixed Effects (LSDV) Estimation

TFP	Coef.	Std. Err.	T	P>|t|
Y/L	0.291	0.012	24.59	0.000
C/L	-0.300	0.013	-22.72	0.000
HEE	0.451	0.117	3.84	0.000
HEG	-0.939	0.237	-3.97	0.000
Countries				
Benin	0.405	0.055	7.41	0.000
Botswana	1.039	0.071	14.56	0.000
Central A.Rep	0.139	0.055	2.52	0.012
Côte d'Ivoire	0.947	0.055	17.29	0.000
Cameroon	0.827	0.055	15.10	0.000
D.R. of Congo	-0.076	0.055	-1.38	0.167
Congo	1.066	0.056	18.88	0.000
Gabon	1.356	0.089	15.24	0.009
Ghana	0.304	0.055	5.55	0.000
Gambia	0.581	0.079	7.31	0.000
Kenya	0.726	0.055	13.13	0.000
Liberia	0.086	0.060	1.43	0.153
Lesotho	0.480	0.069	6.95	0.000
Mali	0.870	0.055	15.91	0.000
Mozambique	0.336	0.055	6.12	0.000
Mauritania	0.915	0.075	12.16	0.000
Mauritius	1.088	0.080	13.67	0.000
Malawi	0.284	0.055	5.21	0.000
Namibia	1.163	0.082	14.17	0.000
Niger	-0.156	0.055	-2.86	0.004
Rwanda	0.743	0.055	13.57	0.000
Senegal	0.495	0.055	9.07	0.000
Sierra Leone	0.794	0.055	14.47	0.000
Swaziland	1.674	0.150	11.18	0.000
Togo	0.319	0.055	5.80	0.000
Uganda	0.536	0.055	9.78	0.000
South Africa	0.976	0.056	17.42	0.000

Zambia	0.549	0.055	10.07	0.000
Zimbabwe	0.643	0.055	11.73	0.000
Cons	-0.406	0.040	-10.19	0.000

Source: Author's Computation, 2018

The results from fixed effects LSDV presented in Table 8 reveal some important information when the findings are compared with the initial outcomes indicated in Table 7. As noted earlier, the use of the fixed effects LSDV is justified by the need to investigate the countries' specific effects in the model as we allow their intercept to vary. Again, the bias resulting from the inconsistent estimator disappears as T becomes large with fairly large N in the LSDV model. In the paper model T=35 and N=30.The value from F statistics is 126.37 and it is statistically different from zero at 5% confidence level. The results also show that 28 of the intercepts (constant inclusive) are individually statistically significant at 1% level of significance. They show that the values of the intercept of 28 of the 30 countries are statistically different from zero. This clearly indicates that there is a high level of country-specific effects in our model; this can be attributed to different countries' leadership style, administration and philosophy on higher education (Gujarati, 2009).

The LSDV result is an extension of the fixed effects results. The test computes the coefficient for dummy variables as intercept or constant for all 30 countries. It also tests their individual statistical significance. It should be noted that the first aspect is the summary result of the fixed effects within regression. The remaining coefficients are the constants which represents dummy variables for each country.

The LSDV results further shows that only three of the 30 countries investigated, Niger, Rwanda and Togo, have constants that are not statistically significant. The reasons for this effect require further investigation. The remaining 27 countries exhibit common significant features with Burundi as the reference point. The implication is that the cross-sectional dependence noted from this result seems to show that the variables are behaving in the right direction and could inform our findings and conclusions from the analysis, especially when supported by a more robust estimating technique. It is evident that almost all the countries under investigation share the same pattern of behavior in terms of the relationship between TFP and the identified explanatory variables.

The value of the R-square in the LSDV is higher than the fixed effects within variation in Table 6. The F-statistic rises significantly, confirming that the fixed effects LSDV model is also significant. The results show that, all the explanatory variables are statistically significant at conventional levels. For instance, the elasticity of outputs per worker in the SSA countries under investigation is positive, indicating a direct relationship between output per worker and TFP. This is normal and conforms to the a priori expectation, as it is statistically significant. It further confirms that this variable contributes to the growth of TFP in the model. A 1% increase in outputs per worker could increase TFP by 29.14%. Since this variable is significant, if higher education can produce more graduates, productivity would improve.

The capital per worker elasticity is negative but statistically significant meaning that capital per worker in the SSA countries under investigation has a significant but negative impact on TFP. The major reason is the peculiar economic situation in the SSA countries as there is imbalance in the capital/ worker ratio, leading to an inverse relationship with TFP. Enrolment in higher education is significant and the coefficient is positive, indicating a direct relationship between enrolment and TFP. Unfortunately, HEE has not received adequate attention in these countries despite its significant impact on productivity. A 1% increase in higher education could considerably increase TFP by 45%. HEG in fixed effects (within) is statistically significant and the coefficient is negative. A similar result is obtained in the LSDV result with no variation as the coefficient is negative. From the fixed effects result, the negative relationship between HEG and TFP leads to a decrease in TFP. This is a clear indication that HEG are not efficiently utilized. Coupled with the LSDV result, this means that HEG is statistically significant but the coefficient in negative. This conflicting result could either be refuted or supported by a more robust dynamic estimation technique.

Finally, the fixed effects LSDV results have the potential to yield a consistent estimator when the T is large and N is also fairly large. According to Arellano and Bond (1991), to obtain an efficient estimator in panel models, the dynamic panel model is preferred. Consequently, we proceed to the system generalized method of moments (SYS-GMM) (Blundell & Bond, 1998). The use of the technique is justified by the need to paper the consistency of our results in dynamic panel models, having determined that the results were consistent in the two previous (although with some slight variation) fixed effects models and the size of our data sample is large enough to accommodate the dynamic model.

4.1.7. Dynamic Panel Data Analysis

Various researchers have emphasized that, while estimates from the static panel data might be consistent, they may not be efficient. In order to conduct an adequate robustness check and as a follow up on the static panel data results, dynamic panel data analysis developed byArellano and Bond (1991) and Blundell and Bond (1998) is employed. This approach is popularly known as Systemic Generalised Method of Moments (SYSGMM) and has been shown to produce efficient results. Consequently, this paper estimates the dynamic panel model for the effects of HEE and HEG on TFP to serve as a robust check for the results obtained under the static panel models (Blundell & Bond, 1998; Uzawa, 1965). The results from the dynamic panel data analysis are presented in Table 9.

The results presented in Table 9 exhibit a slight variation from the initial results obtained from the static panel model of fixed effects least square dummy variables model only in the negative constant. They show no variation in terms of the effects of the nature of the relationship between HEE and HEG on TFP or the significance of each determinant although there are some slight dissimilarities. Notwithstanding this, the dynamic panel SYSGMM offers consistent and robust results to corroborate the paper's other results. Efforts are made to explain those areas with slight differences from what was obtained under the static panel models.

Firstly, the signs of the variables coefficients indicate no variations; for instance, in both the static and dynamic models, output per worker and capital per worker have similar signs of coefficients; while output per worker is positively signed, capital per worker is not. The same condition holds in the case of HEE and HEG. Enrolment is positively signed in both the static model and the dynamic model. HEG is negatively signed in the static and SYSGMM models. The additional information in system GMM is the significant and positive relationship flowing from the lag of TFP to its dependent variable, indicating that there is consistent relationship from the past period of TFP to the present.

Table 9. Results from System GMM Regression

Group variable: id			Number of obs= 1050			
Time variable: year			Number of groups = 30			
Number of instruments = 24			Obs per group: min = 35			
Wald chi2(5) = 12306.39			avg = 35.00			
Prob> chi2 = 0.000			max = 35			
Variables	Coeff	Correc std.Err	Z	P>|z|	[95% Conf. Interval]	
TFP						
L1.	0.860	.0555	55.34	0.000	0.901	0.967
CL	-0.075	.0126	-2.10	0.036	-0.051	-0.002
YL	0.089	.0144	2.12	0.034	0.002	0.059
HEE	0.142	0.022	3.99	0.000	0.044	0.131
HEG	-0.332	0.050	-3.45	0.001	-0.271	-0.074
Cons	-0.084	0.011	-3.06	0.002	-.053	-0.012

Source: Author's Computation, 2018

4.1.8. Analysis of Findings

The results of SYS-GMM in Table 9 strongly confirm our claims from the previous estimated models. This clearly indicates consistency of our results among the various models estimated. Indeed, the dynamic panel model strongly supported this claim and we obtained statistical significance at 1% level in the fixed, LSDV and SYSTEM GMM. Fixed effects within group estimation, fixed effects LSDV and the dynamic SYS-GMM model all exhibit similar direction in coefficients' signs in all the models and the SYS-GMM results, which according to the literature produce the most reliable parameter estimates, confirm the statistical significance of all the parameter coefficients.

Output per worker and HEE are significant and positively related to TFP. This result is expected as it conforms to the a priori expectation and is in line with human capital theory which is the basis of this research. This indicates that the higher the output per worker and HEE in the SSA region, the stronger the effects on TFP growth. This corroborates the computed average TFP graph in Figures 2.4-2.10 with a mix of weak and negative TFP. Taking the state of output per worker and HEE among SSA countries into consideration, this result is a true reflection of the region's productivity condition. The implication is that HEE could positively influence TFP in the 30 SSA countries if policies are adopted to create a productivity-friendly environment for young graduates. Again, outputs per worker which exhibits the expected positive relationship with TFP means that HEE could combine with outputs per unit of labour to generate increased productivity effects.

Again, HEG and capital per worker consistently exhibit a negative significant relationship with TFP. The result for capital per worker and HEG negates the a priori expectation and the extant human capital theory; however, it is strongly supported by the screening hypothesis. Although unexpected, this appears to reflect the true SSA condition. For instance, the coefficient of HEG under systemic GMM is -.3319098. This implies that a unit rise in HEG will lead to an approximate 33.19% decrease in TFP in the SSA countries under investigation if graduates are not put to efficient use. As confirmed in the literature, negative economic activities that are not accounted for in national accounting could hamper the growth of TFP, since they do not substantively contribute to the economy. The only difference in the results obtained from all the models lies in the significance of the parameter estimates and constant.

4.1.9. Inferences, Comparison with Previous Empirical Studies and Discussion of the Findings

In this paper the impacts of higher education (both HEE and HEG) on TFP appear mixed. Higher education human capital proxied by enrollment and graduates consistently shows negative and positive signs in both methods of estimation. The human capital effects on TFP among the SSA countries flow from positive to negative as the regression moves from HEE to HEG. This result negates human capital theory as we expect that it should be positively related to TFP. On the other hand, HEG and output per worker adequately conforms to human capital theory but negates the screening theory. The inverse relationship between capital per labour and TFP theoretically concurs with arguments with regard to capital-labour disaggregation. This theory suggests that technological progress is only possible among nations with appropriate capital intensity margins, otherwise known as capital-labour ratios. Countries with low capital-labour ratios may not benefit from technology spillovers if innovation takes place at high capital-labour ratios, and such ratios may thus cause them to fall behind. A retrospective look clears any doubt about the impacts of higher education on productivity enhancement in the SSA countries under investigation. Miller and Upadhyay (2002) recorded the negative impact of human capital on TFP among high-income nations and positive impacts among middle-income nations. Pritchett (2001) drew attention to the remarkable and statistically significant negative effects of human capital on TFP growth. Caselli and Colemans (2006) quantitative analysis clearly indicates that higher education human capital is not a significant positive factor in determinant TFP. As SSA countries are still primarily agro-based and hi-tech industrial activities are at a low level, higher education should be less influential. As argued by the literature, the existence of low HEE is evident in low TFP growth. This fact has been empirically supported by our models and supports the views of several studies that used different education variables and analysis to confirm the existence of a positive relationship between education and productivity (Artadi & Sala-i-Martin, 2003; Diebolt, Haupert & Goldin; Mohamed, 2013). The paper consistently confirms the negative effects of HEG on TFP as this variable is statistically significant in the dynamic panel model and in the static models. The finding is supported by Barro (2001) Barro and Lee (2013) and Pritchett (2001), who concluded that education has a negative impact on TFP.

Given the results on the impact of HEG on TFP, the main concern is why HEG does not positively influence SSA countries' TFP.Various possible explanations have been offered. For instance, various fields of paper at higher education level could promote growth on condition that this is not "over-supplied" compared to a country's socio-economic needs. In addition, qualitative elements such as decision-makers' lack of willingness to embrace formal knowledge could go a long way in explaining variations in higher education's influence on productivity growth among the SSA countries under investigation. The literatures notes, that the talent held by highly educated individuals has significant effects on countries' productivity. Ali, Egbetokun, and Memon (2016) argue that most talented people trigger productivity in others, so that their potential advantage could be spread on a larger scale. When such individuals establish organisations and firms, they have the potential to grow faster through innovation. By the time they become rent seekers, they focus on wealth and this causes productivity to decline. The choice of occupation largely depends on employment packages, market size, to scale in each sector and on returns on ability. Among the nations of the world, talent is rewarded more by rent seeking than entrepreneurship, leading to stagnation. Studies have shown that nations that produce larger numbers of engineering graduates have a greater possibility of recording higher levels of productivity than those that produce more law graduates. Thus, Blundell, et al (2001) conclude that the allocation of talent determines productivity especially when a specific higher education skill is under or over supplied in the economy, eventually leading to a decline in graduates' productivity. Boianovsky and Hoover (2009) also posit that any higher education productivity effect depends on the efficiency with which skilled labour for productive activities is allocated by labour markets as well as whether or not higher education promotes productivity enhancement. These arguments could explain the mixed results on the impact of higher education on TFP. As noted earlier, the SSA countries under investigation are primarily agriculturally-based economies with insufficient ability to accommodate the level of higher education that its human resources require. As the industrial sector is underdeveloped in these countries, this increases the market for the increasing number of HEG. According to Isaksson (2009), established institutions are required for TFP to be positively impacted by HEG and this is a major constraint among the SSA countries.

4.1.9.1. Test for over-Identification and Serial Correlation in the Dynamic Panel Data

In this section we test for the validity of the instruments adopted in the paper's model. This is done using the Sargan test, although Roodman (2009) has questioned the appropriateness of this test when large numbers of instruments are involved. However, what constitutes too many instruments has not been clearly and adequately defined (Ruud, 2000). The two most acceptable conditions for the adoption of appropriate instrumental variables are that of their correlation to the endogenous variable(s) and orthogonality with the error term. The given valid moment conditions in the systemic dynamic panel data results are the means to produce the correct results. The moment conditions' validity can only be tested on the condition of over-identification and this can only be tested if they are un-identified in the model. The over-identifying restrictions validity affirms the Sargan test's null hypothesis.

The literature notes, that over-identification is a common problem associated with dynamic panel data in SYSGMM. The identified problem in the regression of system GMM is connected to the behaviour of the finite sample in the SYSTEM GMM estimator and this finite behaviouris often affected by two major factors, the number of moment conditions and the strength of identification (Arvanitidis, Pavleas & Petrakos, 2009). The most recent test available in the literature for the validity of the identification problem is the Hassen /Sagan test also known as the J test. In a situation of weak moments asymptotic, even when the number of instruments is large in the cross sectional regression, this test has been proven to be valid (Kwon, 2009; Wong, 2012). In addition, the presence of autocorrelation of serial correlation in the dynamic panel data estimates has been identified as one of the major challenges confronting dynamic panel data estimators. The implication is that the efficiency of SYSGMM estimators is limited (Arvanitidis et al., 2009). The findings on the over-identification test and the test for serial correlation are presented in Tables 11 and 12 respectively.

Table 10. Sargan test of over-identifying restrictions

H0: over-identifying restrictions are valid	
chi2(18)	23.60
Prob > chi2	0.169

Source: Author's Computation, 2018

From this result, it shows that we fail to reject the null hypothesis; therefore, over-identifying restrictions are invalid. The implication is that the number of instruments used in the SYSGMM estimation does not have any negative effect on the estimators of the SYSGMM. The closer the P-value is to one, the better; thus, the result is adequate to establish no over-identifying restriction. Again, the number of instruments does not exceed the number of countries. Based on the model diagnostics, the Arellano-Bond SYSGMM estimator produces the best estimates at AR (2). At the level of AR (1) estimation, a level of serial correlation could be expected which is corrected at AR (2).Therefore, the level of significance may be allowed at AR(1) but not at AR(2). Again, the number of instruments is less than the number of groups and finally, the overall P-value is significant.

Table 11. Hansen test of over-identifying restrictions

H0: over-identifying restrictions are valid	
chi2(18)	22.28
Prob> chi2	0.220

Source: Author's Computation 2018

Table 12. Result on Serial Correlation

Arellano-Bond test for AR(1)	z =-2.77	Pr > z =0.006
Arellano-Bond test for AR(2)	z =-1.28	Pr > z =0.201

Source: Author's Computation, 2018

This section addresses the concerns of policy makers and education stakeholders with respect to higher education's impacts on productivity from the perspective of the productivity gap between countries with higher education and those without it, with special emphasis on the 30 SSA countries.

Conclusion and Recommendations

The findings from these analyses show that both HEE and HEG have significant impacts on TFP. While HEE has a positive effect on TFP, an inverse relationship exists with HEG. Given the diagnostic checks conducted in this paper, the robustness of our results has been established. The hypothesis that HEE and HEG have a significant positive impact on productivity in the selected SSA countries has been proved. The result which indicates that HEE has a positive relationship with TFP is supported both theoretically and empirically by studies in countries across other regions of the world. Furthermore, the inverse effect of HEG on TFP, which seems unexpected, is a true reflection of the state of HEG in the region. The effects of education on productivity have been extensively explored in the literature. This paper contributes to this literature in three important ways. Firstly, we integrated HEE and HEG in the productivity effects model. Previously, these were used individually. This enabled us to highlight the drop-out rate as a possible factor influencing the divergent results in the literature on the individual relationships between HEE and productivity and HEG and productivity. To the best of our knowledge, this is the first paper that integrates these two concepts. Secondly, we provide evidence to support a negative relationship between HEG and productivity, and a positive relationship between HEE and productivity. Finally, we measured the productivity gap of countries in the SSA region with a simple model adopted from De la Fuente (2011) which was applied to the worldwide frontier. This has not been previously done for the SSA region.

The major constraint in the paper was the limited availability of TFP data. We were only able to find such data for 30 of the 46 countries in the SSA region. Using the results to make generalized conclusions about the entire SSA region is contestable and opens the paper to criticism. This is an unavoidable limitation to the paper. Furthermore, efforts to compute TFP for the SSA region from the estimation of residuals in the Cobb-Douglas production function were constrained by the HEG variable.

Further important inferences can be drawn. The analysis revealed that the 30 countries investigated in this paper did not exhibit much variation in the relationship between HEE, HEG and productivity. This is established from the results of the descriptive statistics, which explicitly revealed a weak significant country-specific effect flowing from HEE and HEG to TFP among these countries. This analysis began with the report of descriptive summary statistics which sketched the results from the data distribution where all the variables maintained a positive relationship with the mean distribution of TFP, capita per worker and outputs per worker closer to the maximum. The implication is that a high level of consistency is displayed by the series as their standard deviation and mean values, perpetually fall within the maximum rather than the minimum range of the value. This shows that the growth of these variables is fairly high during the reviewed period. On the other hand, HEE and HEG are closer to the minimum than the maximum, meaning that these two variables are also performing well as the comparatively low value found in the standard deviations shows that only a small amount of deviation from their mean value is found in the actual data. These results were corroborated by the correlation matrix where all the explanatory variables have a weak relationship with TFP; hence, the result is free from the problem of multi-colinearity.

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