# HUMAN CAPITAL IN THE SUB SAHARAN AFRICAN COUNTRIES: PRODUCTIVITY AND THE POLICY IMPLICATIONS*

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**Abstract:** The paper investigates the contribution of Human capital to productivity in SSA countries. Human capital in this paper was viewed concurrently from the perspective of enrolment and graduates of higher education. While adopts panel data of 30 countries for 1980 to 2015 to estimate the paper's models, a systematic procedure involving fixed effect Least Square Dummy Variable (LSDV) and system Generalized Methods of Moments (GMM) were used to test the hypothesis in this paper. Findings from this paper indicates that 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. Quality HEG is recommended so that innovation and skills acquisition add value to SSA higher education. We can also conclude that the level of investment in SSA higher education is grossly inadequate. This implies that these countries' higher education sectors suffer from inadequate human capital.
**Keywords:** Human Capital, Productivity, Sub Saharan Africa, Higher Education Enrolment.

## 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, and 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 sq. km), India (2.97 sq. km) and the United States of America (USA) (9.1 sq. km) and is five times bigger than the 28 nations in the European Union. The SSA population is estimated at more than 930 million, twice that of the European Union. The World Bank notes that there are 46 countries in the region (CIA, 2017; "World Map 2017," 2017). While this profile should give the SSA region a competitive edge, evidence from the extant literature shows a reverse in economic fortunes, calling for urgent higher education policy interventions, among others, to boost HEE and thus human capital formation and productivity in the region (Olamosu & Andy, 2015).

Poor human capital formation and low productivity is evidence that the SSA countries have made little progress in raising their levels of education in general and higher education in particular (Glewwe et al., 2014).

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The SSA region will not meet the demands of the 21st century economy and sustainable economic growth without a well-educated workforce and higher productivity. Productivity can be improved through improved HEE and value, and efficient production processes (Adewunmi, 2011).

Based on this background, there is a need to examine and quantify poor economic performance and low productivity in the SSA economy and reverse this situation by raising the educational qualifications of the workforce. These are major policy concerns in this region. The development of human capital, productivity growth and HEE thus lie at the center of this paper as they are hypothesized to be the major conventional economic indicators of a region or country. Hence the objectives of this paper is to determine the productivity effects of HEE and HEG in the SSA countries. The hypothesis of this paper is stated as follows: H0: HEE and HEG have no significant positive effect on productivity in the selected SSA countries. A systematic procedure involving fixed effect Least Square Dummy Variable (LSDV) and system Generalized Methods of Moments (GMM) are used to test the hypothesis. HA: HEE and HEG have significant positive effect on productivity in the selected SSA countries. A systematic procedure involving fixed effect Least Square Dummy Variable (LSDV) and system Generalized Methods of Moments (GMM) was used to test the hypothesis.

## 2 Human Capital in the Sub Saharan African Countries: Theoretical Foundation

The main argument on this paper is the impact of higher education human capital (as disaggregated by HEE and HEG) on productivity as partly premised on Lucas' (1988) assumption that, apart from the physical capital stock, there exists a hypothetical variable in the productivity model otherwise known as human capital (h), which can be fractionally disaggregated such that a fraction "u" is devoted to the actualisation of the production process while the remainder is devoted to accumulation of human capital. Lucas (1988) therefore argues that the level of total factor productivity (TFP) in the economy is determined by the average level of human capital that produces it. Mankiw et al. (1990) developed a similar model and noted that productivity growth depends on the number of people devoting their time to the accumulation of new ideas and the existing stock of ideas. On the other hand, human capital theory, originated by Becker (1962) argued that education enhances productivity due to the correlation between education and improved wages. The signaling theory pioneered by Spence (1973) opposed this notion, but that scholar noted that earnings could increase in response to higher education not due to any impact on productivity but simply as a result of higher education acting as a signal for productivity. Employers anticipate correlation between higher education and productivity and are thus prepared to pay more to those with such education. This would be verified in real life if workers with higher education are more productive. Individuals with higher education will fulfil this expectation provided that the acquisition cost of higher education is lower for high productivity employees than it is for less productive ones. Therefore, all things being equal, the true market situation would be reflected by an equilibrium separation where an individual with higher productive capacity indicates a greater preference for higher education than workers that are less productive and in turn receives higher wages (Chevalier, Harmon, Walker, & Zhu, 2004).

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. The further a state is from the frontier, the greater the benefits of this catch-up. Benhabib and Spiegel (1994) note that a more educated labour force would also innovate at a faster rate. Lucas (1988) and Mankiw, Romer and Weil (1992) observe that the accumulation of human capital could increase the productivity of other factors and thereby raise productivity growth. These scholars present different perspectives on why the stock of human capital, its rate of accumulation, and the distance to the technological frontier affect productivity.Therefore, human capital matters in productivity in an economy. In order to establish that human capital is an important factor that stimulates productivity through technological progress, Gu and Wong (2012) linked the level of TFP to the stock of human capital, such that A = A (H) where A > 0.

However, there are mixed opinions on the relationship between education, human capital and productivity. Pritchett (2001) asserts that educational growth and growth in outputs are barely visible. He found that education capital had insignificant and negative effects on growth in outputs per capita. On the other hand, Gyimah-Brempong et al. (2006) argue that the income growth effect in Africa is the outcome of the stock of higher education human capital. This paper examines the possible effects that HEE and human capital have on productivity in SSA countries.

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, leading to the adoption of new technologies and improved economic performance. However, it appears that the empirical evidence has not always been consistent in this theoretical model. Moreover, empirical evidence to test this assumption in SSA countries has not yielded consistent results. The negative results reported in some studies have led scholars to question the functional role played by education in the productivity process. Some of their findings are highlighted in this section.

## 3 Human Capital in the Sub Saharan African Countries: Empirical Studies

Empirical studies on productivity and related variables across countries are summarised in this section.

Baier, Dwyer, and Tamura (2006) conducted extensive studies across 145 countries using data that span more than 100 years to investigate the relative significance of human capital and physical capital growth to TFP. Using a growth accounting framework, the results indicate that only 3% of TFP growth was explained by average outputs growth per worker. Further examination confirmed remarkable variations across regions. Among the nine regions examined, growth in TFP accounts for an average of 20% of growth in outputs in three regions and within the range of 0-10 % across three other regions. A further three regions showed negative average TFP growth. Extant theories were adopted by the researchers to develop estimates of the comparable significance of the variance in TFP growth and aggregate input growth for the cross countries output growth. The average variation in aggregate input growth per worker across all countries accounted for about 35% of the variance in the cross countries outputs growth per worker. Total variation in TFP growth explained about 87% of variance. Negative TFP growth accounted for more important variance of TFP growth in the paper.

Miller & Upadhyay, (2002) questioned, do openness and human capital accumulation promote economic growth? While intuition would suggest that this is the case, the existing empirical evidence provides mixed support for such an assertion. They examined Cobb-Douglas production function specifications for a 30-year panel of 83 countries representing all regions of the world and all income groups. They estimated and compared labour and capital elasticity of output per worker across each of several income and geographic groups, finding significant differences in production technology. Then they estimated the total factor productivity series for each classification. Using determinants of total factor productivity that include, among many others, human capital, openness, and distortion of domestic prices relative to world prices, they found significant differences in the results of the overall sample and sub-samples of countries. In particular, a policy of outward orientation may or may not promote growth in specific country groups, even if geared to reduce price distortion and increase openness. Human capital plays a smaller role in enhancing growth through TFP.

Alvi and Ahmed (2014) investigated the effects of education and health on TFP using panel data analysis for 37 developed and developing economies over the period 1990 to 2010. In their two-step methodology, the Cobb-Douglas production function is structured in order to derive the first step measure of TFP. To highlight health and education indicators, the second step empirically established what determines TFP. Life expectancy and average years of schooling were used as health and education indicators, respectively. The fixed and random effects approach was adopted as the estimating technique. The outcome of the research suggests that both health and education have a positive, significant and robust impact on TFP. This highlights the importance of improving health and education through policy implementation so as to ensure long-run sustainable economic growth.

De la Feunte (2011) used average years of schooling as a proxy for human capital and biennial data for the summary period 1965-1995 to examine the effects of human capital on productivity among some OECD countries. Linking the Cobb-Douglas production function to the technical progress function, the paper found that human capital has a large and positive coefficient value; the coefficient for Spain was higher than for the 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 (Pritchett, 2001).

Nachega and Fontaine (2006) examined the factors that determine growth in TFP in Niger between 1963 and 2003. The emphasis in this research is 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 shows 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**.**

Aggrey, Eliab & Joseph, (2010) investigated the effect of human capital on labour productivity in SSA manufacturing firms using firm level panel data analysis. The first limitation of this paper is that it only covered three of the 46 countries in the SSA region. Uganda, Kenya and Tanzania were used as case studies and the GLS panel estimation showed that the proportion of skilled workers and average education had the most significant impact on manufacturing productivity in these countries. The fact that investment in education and human capital and their contribution to productivity growth in SSA countries continue to receive minimal attention among researchers explains the uniqueness of the research presented in this chapter.

# 4 Methodology

## Model Specification

Here, we begin with empirical analysis of the link between the Cobb-Douglas production function and the technical progress function as a methodology adopted from De la Feunte (2011), 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:

$$Y_{it} = A_{it}\, K_{it}^{\alpha k} H_{it}^{\alpha h} L_{it}^{\alpha l} \qquad (4.1)$$

where: $Y_{it}$ = Total outputs 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 $\alpha_i$ (with $I = k,h,l$).

First, we provide for labour 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 eq.1 through by total employment L yields:

$$Q_{it} = AZ_{it}^{\alpha z}\, W_{it}^{\alpha w} \qquad (4.2)$$

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

$$Y_{it} = A_{it}\, K_{it}^{\alpha k}\, HEE_{it}^{\alpha hee} HEG^{\alpha heg} L_{it}^{\alpha l} \qquad (4.3)$$

With constant return to scale ($\alpha k+\alpha hee+\alpha heg+\alpha l =1$), 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:

$$Y_{it} = a_{it} + \alpha k(k_{it}) + \alpha hee(HEE)_{it} + \alpha heg(HEG)_{it} - \mu_{it} \qquad (4.4)$$

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

$$A_{it} = Y_{it} - \alpha k(K_{it}) - \alpha hee(HEE_{it}) - \alpha heg(HEG_{it}) - \mu_{it} \qquad (4.5)$$

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

$$A_{it} = Y_{it} - A_{it-1} - \alpha k(K_{it}) - \alpha hee(HEE_{it}) - \alpha heg(HEG_{it}) - \mu_{it} \qquad (4.6)$$

**Estimating Technique**

Basically, models in panel are two division: 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 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; consistent estimation means that the values around their various sample means are differenced (Blundell, Bond, & Windmeijer, 2001).

**Summary Procedures (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 a panel model. This approach was been 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 thus:

$$a_{it} = \beta_{it} + \rho a_{it-1} - \beta_2 k_{2it} - \beta_3 hee_{3it} - \beta_4 heo_{4it} - \mu_{it} \qquad (4.11)$$

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:

$$\Delta a_{it} = \beta_1 + \rho \Delta a_{it-1} - \beta_2 \Delta k_{2it} - \beta_3 \Delta hee_{3it} - \beta_4 \Delta heo_{4it} - \Delta \psi_{it} \qquad (4.12)$$

In order to avoid possible correlation between $a_{it-1}$ and $\psi_{it}$, 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:

$$Z\Delta\, y_{it}\ Z'\Delta a_{it} = \beta_1 + Z'(\Delta a_{it-1})\rho - Z'(x_{it})\beta - Z'\Delta\psi_{it} \qquad (4.13)$$

Estimating equation (4.13) 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.

**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 identify 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 inputs. 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.

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 enrol 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.

**Data Sources**

This paper adopts panel data of 30 countries for 1980 to 2015 to estimate the paper's models. 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.

**Data Analysis and Model Estimation**

***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 below. All the P-values are shown at 1% level of significance.

**Table 18.1: 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

***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 18.2: Summary Descriptive Statistics on series TFP as dependent variable and CL, YL, HEE, HEG**

| 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 4.2 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.

***Correlation Matrix on productivity effects of higher education***

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

**Table 18.3: Correlation Matrix on TFP as dependent variable and CL, YL, HEE, HEG**

| 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 4.3 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 4.2.

This is an interesting result as it indicates that the variables in our estimation do not suffer from the problem of multi-colinearity.

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 4.4 below.

***Panel estimation results***

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 paper 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 18.4: Ordinary Least Square regression Result on TFP as dependent variable, CL,YL, HEE, HEG**

| 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

***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 18.5: Random Effects (within variation regression) Estimation Results**

***Dependent variable: Total Factor Productivity (TFP)**

| 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

***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 18.6: Fixed Effects (within variation regression) Estimation Results.**

***Dependent variable: Total Factor Productivity (*TFP*)**

| *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, 2017

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

Prob>F = 0.0000

***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 18.7: 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 4.5 and 4.6 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 4.7, it is obvious that there is an inverse relationship between TFP 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.

***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 18.8: Fixed Effects (LSDV) Estimation. *Dependent variable: Total Factor Productivity (TFP)**

| *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 4.8 reveal some important information when the findings are compared with the initial outcomes indicated in Table 4.7. 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 4.6. 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.

***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 and Bond, 1998; Uzawa, 1965). The results from the dynamic panel data analysis are presented in Table 4.9.

The results presented in Table 4.9 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 18.9: Results from System GMM Regression**

<table>
<tr><td colspan="3">Group variable: id</td><td colspan="4">Number of obs = 1050</td></tr>
<tr><td colspan="3">Time variable: year</td><td colspan="4">Number of groups = 30</td></tr>
<tr><td colspan="3">Number of instruments = 24</td><td colspan="4">Obs per group: min = 35</td></tr>
<tr><td colspan="3">Wald chi2(5) = 12306.39</td><td colspan="4">avg = 35.00</td></tr>
<tr><td colspan="3">Prob> chi2 = 0.000</td><td colspan="4">max = 35</td></tr>
<tr><td>Variables</td><td>Coeff</td><td>Correc std.Err</td><td>Z</td><td>P>|z|</td><td colspan="2">[95% Conf. Interval]</td></tr>
<tr><td>TFP</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>L1.</td><td>0.860</td><td>.0555</td><td>55.34</td><td>0.000</td><td>0.901</td><td>0.967</td></tr>
<tr><td>CL</td><td>-0.075</td><td>.0126</td><td>-2.10</td><td>0.036</td><td>-0.051</td><td>-0.002</td></tr>
<tr><td>YL</td><td>0.089</td><td>.0144</td><td>2.12</td><td>0.034</td><td>0.002</td><td>0.059</td></tr>
<tr><td>HEE</td><td>0.142</td><td>0.022</td><td>3.99</td><td>0.000</td><td>0.044</td><td>0.131</td></tr>
<tr><td>HEG</td><td>-0.332</td><td>0.050</td><td>-3.45</td><td>0.001</td><td>-0.271</td><td>-0.074</td></tr>
<tr><td>Cons</td><td>-0.084</td><td>0.011</td><td>-3.06</td><td>0.002</td><td>-.053</td><td>-0.012</td></tr>
</table>

Source: Author's Computation, 2018

**Analysis of Findings**

The results of SYS-GMM in Table 4.9 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.

**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 Coleman's (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.

**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 behaviour is 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 4.11 and 4.12 respectively.

**Table 18.10: 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 18.11: 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 18.12 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.

## 5 Summary, Recommendations and Conclusion

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 total TFP; hence, the result is free from the problem of multi-colinearity.

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