Higher Education Enrolment in Sub-Saharan Africa: Determinants and Policy Implications

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Abstract

This paper investigates the factors that determine higher education enrolment (HEE) in selected sub-Saharan African (SSA) countries over the period 1980-2015. The hypothesis of the paper is that certain factors have significant positive effects on HEE in the region. A Panel Auto Regressive Distributive Lag (P-ARDL) is adopted as the estimating technique and the results suggest that there is no long- or short-run relationship between HEE and GDP per capita. Furthermore, while the impact of variables such as secondary school graduates (SSG), population growth rate (PGT) and employment rate (EMR) on HEE is positive and significant in the long run, the reverse is true for population age group (PAG). Short-run causality tests conducted to detect if pairs of independent variables would jointly affect HEE suggest that the results are reliable. The error correction model (ECM) value of -0.024202 suggests a possible 2.4% speed of adjustment in the system from the short-run deviation to the long-run equilibrium. These results imply that improvement is possible in HEE in the long run if policy makers act on the identified variables of interest.

Keywords: Sub-Saharan Africa, P-ARDL, Higher Education Enrolment

Gel Code*: I21, I23*

1 Introduction

Between 1980 and 2010, sub-Saharan African (SSA) countries witnessed low levels of economic growth, productivity and higher education enrolment (HEE) (Glewwe et al., 2014). The region covers a large portion (22 million square 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 million square km) and is five times bigger than the 28 nations in the European Union (EU). The SSA population is estimated at more than 930 million, twice that of the EU. 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 and Andy, 2015).

According to Bloom et al. (2014), the average HEE rate of 7% in the SSA is the lowest among the world's regions. Glick and Sahn (2000) argue that this is due to the fact that developing economies are unable to absorb higher education graduates. Another reason cited in the literature is the colonial legacy, which arguably deprived many Africans of decent and attractive higher education (Glick and Sahn, 2000). In addition, the World Bank has focused on primary education and neglected the development of the higher education sector. As universal primary education expanded, studies reported growing concerns about inefficient allocation of resources amongst the different education levels (Tilak, 2005). It has also been argued that the laissez-faire principles in the higher education sector, through the invisible forces of demand and supply (Tilak, 2005), worsened HEE due to imperfect market forces in the SSA region (Wong, 2012) and that the low levels of literacy among school-leavers contributed to lower levels of HEE (Sawyerr, 2002).

Statistics also show that growth in HEE in the SSA region has not matched the growth of the population eligible for enrolment (18-23 years). In 1999, HEE in the SSA region grew by 4%, while the population of young people eligible for enrolment increased by 19%. The comparable figures for 2008 were a 6% increase in HEE, and a 27% growth in the population of eligible individuals in this age group (United Nations, 2011). It is worth noting that the growth of the eligible population for HEE is expected to continue, with the United Nations (2011) estimating that the 18-23 age group in SSA countries will grow to more than 100 million by 2030. This suggests that there will be far more students eligible for higher education, but with limited access to such education, posing a challenge to the region's policy makers.

Figure 1 below compares HEE in the SSA region to other regions. It clearly shows that SSA lags behind the rest of the world, with the most recent enrolment ratio in the region estimated at 10 to 100.

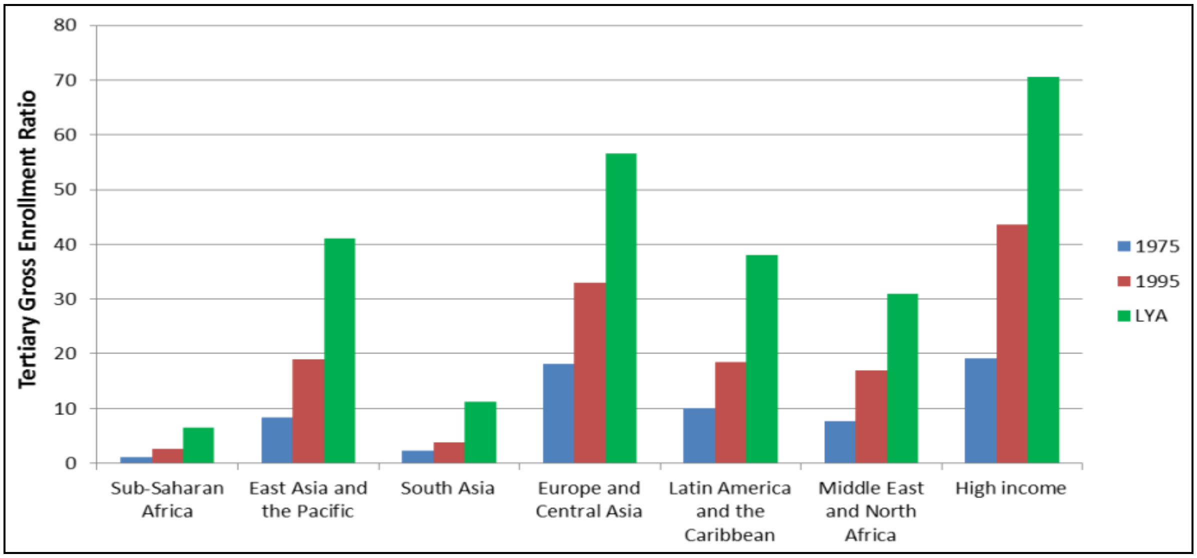

Figure 1: Economic Regions of the World and their Higher Education Enrolment Ranking

Note: LYA (latest year available) for most countries is 2010, ranging from 2005 to2010.
Source: Bloom et al. (2014).

From a policy perspective, this is a serious situation as it implies that the region lacks the skills and knowledge required to contribute to the growth of the regional economy. Indeed, the literature posits that the stock of knowledge and skills in a given region are essential for socio-economic and technological development in that region (Bloom, et al.,2014). The circumstances in SSA thus call for urgent higher education policy intervention (Glewwe et al., 2014). However, any intervention would require solid evidence on the factors that determine HEE. Hence, this paper examines the factors that determine HEE in the region and the extent to which they have affected the growth rates of HEE in SSA countries. It uses the Panel Auto Regressive Distributive Lag (P-ARDL) to identify such factors and to test hypotheses. It is believed that this will assist policy-making with regard to HEE in the region.

2. Literature Review

2.1 Determinants of Higher Education Enrolment: Theoretical Framework

Empirical analyses of HEE need to adequately relate to theories which view education as investment rather than consumption goods[1]. The central proposition of human capital theory is that an individual with higher levels of educational attainment has more capacity and higher labour productivity than a less educated employee. Economic theory regards a human being as a capital good and expenditure on education has been considered as a kind of investment as foregone wages and time are expected to yield future benefits in the form of productivity and income.

As noted previously, there is increasing pressure on policy makers in SSA countries to increase HEE in the region. This is due to recognition that this sector is an engine of economic transformation and the development of higher levels of human capital among the youthful population. However, efforts by stakeholders in the region to increase HEE rates appear to have been unsuccessful. This could be due to the limited empirical evidence on the factors that promote an increase in HEE in the region. Given the homogenous economic systems and integration enjoyed among countries in the SSA region, the lack of panel study evidence on this issue is puzzling. This could explain the policy mismatch between higher education and the drivers of its enrolment as well as the widening gap in HEE between SSA and the rest of the world.

It has been hypothesised that certain variables determine HEE at individual country level. However, the role played by these variables, notably population age group, economic factors, population growth rate, parental education, and village-level income has only been verified in a few regions among developed economies (see, for example, Sojkin et al., 2012). The factors that determine HEE in SSA have not been investigated and generalising from the findings of research conducted elsewhere could be misleading, at least from a policy point of view. This study thus fills a gap in the literature by examining the factors that determine HEE in the SSA region.

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[1]One of the prominent theories in this respect is the theory on the consumption of HEE (Foot and Pervin, 1983). This theory views higher education from the perspective of a normal consumer good. It argues that demand for higher education is a relative function of higher education price as well consumers' income. The Cohort Size theory originally formulated by Easterlin (1980) posits that, the economic and social fortunes of a cohort (those born in a given year) tend to vary as a function of its relative size, approximated by the crude birth rate. The global youthful population has increased since World War II. Finally, Boudon (1974) examined why students from lower socio-economic groups struggle to gain entry to tertiary education even though they demonstrate high levels of performance in secondary school. Disparity in school performance among social classes has been tagged 'primary' (sibling) effects, while that in access to educational levels despite the same relative school performance is called 'secondary' effects.

A variety of methods have been used to investigate the determinants of higher educational achievement. Constant Elasticity of Substitution (CES), the generalized quadratic form model, Leontief form model, and Cobb Douglass production have been the most common approaches. However, some of these models require certain complex procedures and detailed data that is only available in developed economies. The SSA region has yet to attain the required level of data availability. In line with similar studies in this area of research, this study adopted the Cobb Douglas production function to achieve its objectives (see, for example, Cuartas and Muniz, 2014; Funmilayo, 2014; Ahiakpor et al., 2014; Vieira and Vieira, 2011). Adoption of this methodology is supported by Gyimah-Brempong and Gyapong (1991, 2006) and Hanushek, (2008) who argue that certain predictor variables could enter the education production function as inputs because they influence the outcome of the educational process. The following section reviews the empirical literature on this topic.

2.2 Determinants of Higher Education Enrolment: Empirical Studies

Empirical studies that have evaluated the factors affecting HEE have focused on economic factors such as income and grants (Cuartas and Muniz, 2014), social factors such as parental education (Connelly and Zhen, 2003), demographic factors (Vu et al., 2012), high school and school age populations and enrolments (Funmilayo, 2014) and broad social, cultural and environmental factors at the regional or community level (Cuartas and Muniz, 2014; Vu et al., 2012). The literature highlights that HEE is an important policy matter, and its determinants have been investigated in Europe (Connelly and Zhen, 2003; Vieira and Vieira, 2012), South America (Vu et al., 2012) and Asia (Hussain and Imran, 2015). These studies used a variety of methods and produced findings that policy makers could act upon to improve HEE. They are summarized in Table 1.

Table 1: Summary of studies on the factors affecting HEE

Authors and Date	Variables	Methodology	Findings
Cuartas and Muniz (2014)	Income, income-related factors such	Econometric panel models from	The study found that the quality of higher education and the languages of the host countries

	as loans and grants, HEE	Statistics Office of the European Communities	appeared to significantly determine HEE.
Connelly and Zhen (2003)	Income, parental education, and village-level income		Country-level income, parental education, and village-level income affected enrolment levels.
Vu et al. (2012)	Average education level, income distribution, fertility, stabilization (demographic factors); regional, individual and social inequalities	Multilevel model on 2009 living standard survey	Enrolment at individual level is affected by rural/urban residence, migrant status, ethnic group, gender and household socio-economic status. At a provincial level, average education level (SSG), income distribution (e.g., GDPP) and fertility stabilization (demographic factors) are important predictors.
Funmilayo (2014)	Student enrolment in universities, the stock of academic staff, stock of non-academic staff, and government funds to universities	Vector auto regressive model and stepwise regression method	The stock of academic staff and funding were found to relate to an increase in enrolment.

Source: Authors' Compilation, 2019

However, these studies were mainly conducted at country level and in regions other than SSA. The only study conducted recently in SSA is one by Funmilayo (2014) which investigated HEE in

Nigeria and its findings cannot guide policy at a regional level. Furthermore, evidence from a panel of countries elsewhere in the world cannot guide HEE policy in SSA due to different educational environments and contexts. Therefore, this paper is an important contribution to the literature in this area of research.

3. Methodology

3.1 Model Specification

The paper adopts a human capital approach using an augmented Cobb Douglas production function to build the education production model. The extension of the model has some precedents in the literature (Chechi, 2006; Fumilayo, 2014; Hanushek, 2008), where the production function was extended beyond a firm's productive resources of labour and capital. One of the main reasons for adopting the education production function is that it allows statistical analysis in relation to higher education outcomes using a set of inputs guided by data availability.

This paper relies primarily on the theoretical formulations of Aghion et al. (1998), among other studies, which argues that a constant return to scale to the production function exists. In line with this argument and following Funmilayo (2014); Ahiakpor et al. (2014); Vieira and Vieira (2011) and Cuartas and Muniz (2014); the model linking HEE_{it}, *GDPP*, *SSG*, *EMR*, *PGT*, *PAG*, and *Lx*p is specified as in equation (3.1):

$$HEE_{\mathrm{it}} = \int GDPP_{it}^{\alpha_1} \cdot SSG_{it}^{\alpha_2} \cdot EMR_{it}^{\alpha_3} \cdot PGT_{it}^{\alpha 4} PAG_{it}^{\alpha 5} . Lxp_{it}^{\alpha 6} \qquad (3.1)$$

where GDPP is *Gdp* per capita, *SSG* is secondary school graduates, *EMR* is employment rate, *PGT* is population growth rate, *PAG* is population age group, and *Lxp* is life expectancy.

The nature of the model in this paper is dynamic; this is partly due to the fact that past year HEE predicts HEE in the current year (due to limited enrolment capacities and possible repeats). Therefore, lagged values of HEE are included on the right hand side together with the explanatory variables to explain HEE for the current year in SSA. The dynamic form of equation (3.1) is explicitly given in equation (3.2):

The linear relationship in equation (3.1) leads to equation 3.2 as follows:

$$\ln HEE_{it} = \ln\alpha_0 + \alpha_1 \ln HEE_{it-1} + \alpha_2 \ln GDPP_{it} + \alpha_3 \ln SSG_{it} + \alpha_4 \ln EMR_{it} + \alpha_5 \ln PGT_{it} + \alpha_6 \ln PAG_{it} + \alpha_7 \ln Lxp_{it} + \mu_{it} \quad (3.2)$$

where: μ_{it} is the part of the rate of growth of enrolment that cannot be explained by the growth of enrolment. α_1-α_6 are partial elasticity of the respective variables. Our expectation from a priori theory in the production function emphasises that α_1, α_2, α_3, α_4,..........α_6, must be positively signed and the linearity of logarithmic transformation allows α_1, α_2, α_3,α_4,....α_6 to estimate the responsiveness of students' enrolment in higher education to changes in the quantity of the six independent variables (Corazzini et al., 1972; Sojkin et al., 2012; Funmilayo, 2014).

The equation (3.2) leads to ARDL model specification as follows:

$$\Delta LnHEE_{it} = c_0 + \sum_{j=1}^{n} \beta_{1j} \ln HEE_{it-j} + \sum_{j=1}^{n} \beta_{2j} \Delta \ln GDPp_{it-j} + \sum_{j=1}^{n} \beta_{3j} \Delta \ln SSG_{it-j} + \sum_{j=1}^{n} \beta_{4j} \Delta \ln EMR_{it-j} + \sum_{j=1}^{n} \beta_{5j} \Delta \ln PGT_{it-j} + \sum_{j=1}^{n} \beta_{6j} \Delta \ln PAG_{it-j} \sum_{j=1}^{n} \beta_{7j} \Delta \ln Lxp_{it-j} + \sigma_1 \ln HEE_{it-1} + \sigma_2 \ln GDPP_{it-1} + \sigma_3 \ln SSG_{it-1} + \sigma_4 \ln EMR_{it-1} + \sigma_5 PGT_{it-1} + \sigma_6 PPAG_{it-1} + \sigma_7 Lxp_{it-1} + U_{it} \text{........(3.3)}$$

In this model, j is used to proxy the number of lags, while the first difference operator is indicated by Δ; constant term in the model is represented by c_0, n is used to represent optimal or maximum lag length., $\beta_{1j-}\beta_{6j}$ have been used to proxy the short-run coefficient for the independent variables, respectively, while U_t is the stochastic. $\sigma_1 - \sigma_6$ are the elasticity coefficients used to proxy the long-run relationship, hence to properly investigate long run nexus through the adoption of the null hypothesis and the application of bound testing, such that; $H_0 : \sigma_1 = \sigma_2 = \sigma_3 = \sigma_4 = \sigma_5 = \sigma_6 = 0$ and the alternate hypothesis: $H_1 : \sigma_1 \neq \sigma_2 \neq \sigma_3 \neq \sigma_4 \neq \sigma_5 \neq \sigma_6 \neq 0$.

3.2 Relevance of the Variables and Definitions used in the Model

In line with Sari et al. (2008), annual data for 30 SSA countries over the period 1980-2015 is employed to examine and determine the long- and short-run relationship between HEE and its determinants in these countries. The variables employed for the model are based on the literature and are briefly defined as follows:

The **dependent variable** (HEE): This is the ratio of total enrolment, regardless of age, to the PAG that officially corresponds with the level of education in each of the SSA countries. The proportion of the 'enrollable' population determines the level of human capital in these countries.

The **independent variables**: These include the variables identified in the literature that determine HEE as shown below:

GDP per capita (GDPP): GDP divided by midyear population. This variable is used because when the economic environment is favourable, it is likely that earnings resulting from this economic benefit will have a spill-over effect on students' enrolment rate (Carla et al., 2007). PGT is the exponential growth rate of midyear population from year *t*-1 to *t*, expressed as a percentage and estimated when birth rate is added and death rate is deducted from the existing population. To a great extent, the GRT of a given population determines HEE in SSA countries (Acaroğlu and Ada, 2014).

Population age group (PAG) in the context of this paper is between the ages of 15 and 24. This age bracket exerts considerable influence on HEE because the quantum of the total number of students in a given country ready for higher education is concentrated in the group. EMR represents the percentage of the working population in an economy. The working age population comprises individuals aged 15 to 64. The proportion of the working age population found to be gainfully employed forms the basic indicator for employment. It influences HEE because the immediate availability of a job offer is a motivator. High levels of unemployment will negatively affect students' enrolment (Carla et al., 2007) because they will be discouraged from studying. SSG represents the proportion of students who enrolled in secondary schools and eventually graduated. This group serves as the 'raw material' that produces the requisite input for HEE. Among EU countries, there was a remarkable growth in HEE between 1975 and 1997. Factors identified that contributed to this growth included secondary school leavers' decision not to stay at home after school completion (Carla, et al., 2004; Carton and De Jong, 2002). Lxp is a variable that is often used to capture health conditions among countries (Alvi and Ahmed, 2013). A healthy generation with a longer life span is more likely to enroll in higher education. It is included among the factors that determine HEE as a control variable, and it is expected that if this index is high, it will have a positive impact on enrolment.

3.3 Data Sources

Data on HEE and secondary school output are interpolated by e-view 9.5 from the Barro and Lee dataset of 1950-2010 and 2015-2040, respectively. Other variables are sourced from the online version of the World Bank development indicators. The paper adopts a similar approach to data selection as that developed by Tang et al. (2008). Data from the Barro and Lee dataset (1950-2010 and 2015-2040) are in five-year averages.

3.4 Limitations of the study

Due to the fact that data was not available for all the countries in the SSA region, the study was conducted among 30 countries which were assumed to be representative, as no specific patterns common to this group of countries alone was observed. Furthermore, inclusion of certain variables could have enhanced the quality of the work, including government expenditure on higher education as a percentage of GDP and parents' level of education, but data for these variables were not readily available. Finally, P-ARDL cannot cope with more than six variables and this was also a limiting factor. Researchers could address these limitations in future studies.

3.5 **Justification for the methodology and estimating technique: P-ARDL**

To model the data appropriately and extract both long- and short-run relationships, the appropriate methodology was determined after a unit root test was conducted. Giles (2013) itemised four conditions that pose challenges to data and subsequently determine the choice of method. These are listed below:

(i) In a case when all variables are integrated of order I(0), the Ordinary Least Square (OLS) model is appropriate. This is the case of stationarity.

(ii) If all variables are non-stationary I(0) but are all stationary at I(1), it is advisable to use VECM as it is a simpler model (Johanson Co-integration Approach).

(iii) Where some variables are stationary at levels I(0) and some are I(1) or when some variables are fractionally integrated leading to some complexity, Auto Regressive Distributive Lag (ARDL) is most appropriate (Chudik and Pesaran, 2013).

4.0 **Empirical Analysis**

This section reports the results of the empirical analysis which encompasses summary statistics, correlation matrix (with the result indicating that the variables under investigation have no multicollinearity; see Appendix A), panel unit root (results of the unit root test showed that all passed the conditions required for the adoption of P-ARDL as proposed by Pesaran and Chudik (2013); see Appendix B).

4.1 Preliminary tests and statistics

P-ARDL regression as proposed by Pesaran and Chudik (2013) is adopted with at least two lags. The process of lag selection is purely system selected with Akaike criterion proven as most preferred. The diagnostics tests and details concerning the criteria for selecting lag two and all other diagnostics tests are available in Appendix C , D, E and F.

For the purpose of the study, we test the hypothesis, which states that the factors that determine HEE do not have a significant, positive impact on the growth of HEE in the selected SSA countries. Theoretical debate on the factors that determine HEE is ongoing. While the theory supporting laissez-faire argues that there has been outright neglect of higher education by the public sector, other theories such as the signaling theory, among others, concur that certain factors determine HEE and hence, policy measures can improve it. Our expectation is that certain factors can determine an increase in HEE in the SSA region, but we depend on our empirical results to ascertain and establish this claim. We start by providing the descriptive statistics of the variables used in our analysis in Table 2.

Table 2: Summary Statistics on the series HEE (Dependent variable): SSG, PGR, PAG, Lxp, LogGDPP, and EMR

Variables	HEE	EMP	LOGGDPP	Lxp	PAG	PGT	SSG
Mean	4.513	2.368	3.464	53.379	1975938.	2.632	10.265
Median	2.877	0.554	3.947	53.544	1030804.	2.714	7.006
Maximum	39.726	24.251	106.280	74.194	15060562	14.046	64.400
Minimum	0.072	0.181	-51.030	27.079	513200	-6.924	0.030
Std. Dev.	4.926	3.659	6.933	7.152	2475804.	1.331	10.822
Skewness	2.985	2.776	1.513	-0.046	2.293	-0.297	2.334

Kurtosis	16.150	11.734	57.726	3.399	8.799	17.503	9.177
Jarque-Bera	9385.328	4819.791	135185.6	7.532	2460.115	9481.510	2697.914
Probability	0.000	0.000	0.000	0.023	0.000	0.000	0.000
Sum	4874.358	2557.896	3741.446	57649.49	2.13E+09	2842.471	11086.00
Sum Sq. Dev.	26186.96	14445.15	51870.85	55199.69	6.61E+15	1911.544	126358.0
Observation	1080	1080	1080	1080	1080	1080	1080

Source: Authors' computation, 2018

The mean results for all the variables used in this paper are presented in the second row of the table. The third and fourth rows record the maximum and minimum values for all the variables. Row five reports the result from standard deviation. In the case of enrolment rates in higher education, which is the dependent variable, we found that the maximum is only 39.72%, and the minimum is as low as 0.072%. The mean of 2.88% is closer to the minimum than the maximum. The claim is strongly confirmed by the standard deviation since it is closer to the mean. This result substantially supports extant a priori expectations in SSA countries, which concur that HEE is low.

It is also noted that the results for all the explanatory variables, namely, employment rates, GDP per capita, life expectancy, population growth rate and secondary school graduates, follow a similar minimum trend as HEE. For instance, the maximum for EMR is 24.25%, whereas the minimum is as low as 0.18% and its mean value of 2.37% is closer to the minimum than the maximum. It can thus be stated that EMR is seriously low among the SSA countries under observation since the standard deviation value of 3.66% substantiated the result of the mean.

Worthy of note is the result for GDP per capita and PAG. The result for GDP per capita growth rate indicates a maximum of 106.28% and its corresponding minimum is -51.03%, whereas the mean value is 3.46%, which is closer to the minimum, as supported by standard deviation value of 6.93. The result not only shows direction to minimum, but is also negative.

The result for population age group (PAG) is the only variable that showcased the maximum rather than the minimum. The maximum is 15,060,562, whereas the minimum is 513,200 with a mean value of 1, 975,938 and corresponding standard deviation of 2, 475,804. It is clear that PAG shares a very wide gap with HEE and hence by implication this result supports a priori expectation. However, the information supplied by the summary statistics is subject to further empirical evidence.

4.2 Analysis of the Findings on the Panel ARDL Dynamic Long- and Short-Run Results

Table 3 presents a summary of the long- and short run results on the determinants of HEE in SSA countries.

Table 3: The Dynamic Panel ARDL Long Run Result for Series: SSG, PGT, PAG, Lxp, LogGDPP, EMR and Dependent Variable HEE

Dependent Variable: DHee			
Method: P- ARDL			
Sample: 1980-2015			
Model selection method: Akaike info criterion (AIC)			
Selected Model: ARDL(2, 2, 2, 1, 2, 0, 1)			
Variable	**Coefficient**	**Std. Error**	**Prob.***
SSG	0.342	0.080	0.000***
PGT	2.180	0.732	0.003***
PAG	-0.000001	0.000	0.025**
Lxp	-0.063	0.099	0.522
LogGDPP	-0.067	0.091	0.460
EMR	0.511	0.249	0.040**
C	-2.176	4.907	0.658
P-ARDL Short-run relationship			
HEE(-1)	1.194	0.030	0.000
HEE(-2)	-0.218	0.030	0.000
SSG	0.0955	0.007	0.000
SSG(-1)	-0.105	0.010	0.000
SSG(-2)	0.018	0.007	0.010
PGT	0.003620	0.021	0.863
PGT(-1)	0.002467	0.029	0.933
PGT(-2)	0.046190	0.021	0.028
PAG	-1.54E-07	3.33E-08	0.000
PAG(-1)	1.33E-07	3.35E-08	0.0001
Lxp	0.083	0.008	0.000
Lxp(-1)	-0.108	0.013	0.000
Lxp(-2)	0.023	0.009	0.008
Log GDPP	-0.002	0.002	0.456
EMR	0.119	0.023	0.000
EMR(-1)	-0.106	0.023	0.000
C	-0.052	0.118	0.659

Source: Authors' computation 2018 Note: *, **, *** represent 1%, 5% and 10%, respectively. R^2 = 0.978; Prob. (F- Statistic) =0.0000; Durbin-Watson Sta =1.992071

The finding from the analysis indicates that SSA GDP per capita is not statistically significant in impacting on HEE in both the short and the long run. Apart from the fact that this result negates our a priori expectation, it can be recalled that, in our summary statistics, GDP per capita is not only closer to the minimum, but also exhibits a negative sign. However, its coefficient establishes that an increase in GDP per capita in both in the short and long run will cause HEE to decline by 6.7% and 0.2% in the short run.

Employment rates (EMR), Population Growth Rates (PGT) and Secondary School Graduates (SSG) all exhibit similar characteristics in the long run both in direction and in the level of significance as they show positive relationships with HEE. This result is expected based on a priori expectation and empirical work. The summary statistics showed that these three variables also displayed a low record trend as the mean is close to the minimum and their standard deviations are not fundamentally different from the mean. More particularly, a positive short-run relationship exists between EMR and HEE at 5% level of significance. A unit increase in the EMR will increase HEE by 51% and 11% in the long and short run, respectively. The lag of EMR in the region exhibits an inverse relationship with HEE in the immediate past period. This reflects that a decrease in HEE in the current period is impacted by an increase in the initial level of EMR in the region. A unit increase in the number of SSG, all things being equal, will increase HEE by 34 members; a 1 unit increase in the number of SSG will result in an average 10-member increase in HEE in the current period, and a 3-member increase in HEE in the past two years; while a 1 unit increase in SSG will decrease HEE by 11 members in the short run in the lag period.

Population age group (PAG) in the regression exhibits a long and short-run negative relationship with HEE. The relationship between HEE and PAG is found to be negative and statistically significant even though the value of the coefficient appears marginal. This further substantiates the result of the summary statistics. However, the last year period exhibits positive effects, showing that a unit change in PAG has caused a marginal value of only a 0.000133 unit increase in HEE. This finding seems not to support the findings of Ahiakpor (2014), but corroborates the United

Nations' (2011) claim. In the long run, PAG will have an inverse relationship with HEE. Lxp in the short run is statistically significant both in the last and the current year; however, its long-run relationship is not. A unit increase in Lxp would increase HEE by 8.3 units in the current period and by 2.3 units in the two past years while a 1 unit increase in the Lxp will decrease HEE by 10.7 units. This result supports Ahiakpor's (2014) findings in Ghana.

4.4: Robustness check of the result

The study further classified all the SSA countries under investigation into high and low GDP per capita. As a robustness check of the results, analyses were conducted on countries with high GDP per capita (HGDPP) that is, with GDP per capita above $1000 and on those with low GDP per capita (LGDPP) that is, with GDP per capita below $1000. This benchmark is in line with the UN bench mark (Statistic Portal, 2017). Twenty-six of the SSA countries under investigation are HGDPP countries while four are LGDPP countries.

Table 4: Long-run regression model in Low GDP per capita countries

Dependent Variable: DHee			
Method: P- ARDL			
Sample: 1980-2015			
Model selection method: Akaike info criterion (AIC)			
Selected Model: ARDL(2, 2, 2, 2, 2, 2, 2)			
Variable	Coefficient	Std. Error	Prob.*
SSG	0.277	0.051	0.000
PGT	0.029	0.047	0.536
PAG	-0.881	0.082	0.000
Lxp	1.798	1.115	0.111
LogGDPP	-0.0001	0.0022	0.956
EMR	0.0178	0.132	0.893

Table 5: Long-run regression model in High GDP per countries

Dependent Variable: DHee			
Method: P- ARDL			
Sample: 1980-2015			
Model selection method: Akaike info criterion (AIC)			
Variable	**Coefficient**	**Std. Error**	**Prob.***
SSG	0.144	0.007	0.000
PGT	0.310078	0.022170	0.000
PAG	0.339	0.030	0.000
Lxp	1.705586	0.485389	0.0005
LogGDPP	-0.014952	0.012	0.22

EMR	-2.42E-05	0.000475	0.959

Tables 4 and 5 reflect the long-run result (see short-run result LGDPP countries are in appendix G). Comparing these results with those in Table 3, it is clear that GDPP was not statistically significant in both sets of results. We also note that variables such Lxp, PGT GDPP and EMR are not statistically significant in LGDPP countries, whilst they were significant in pooled data. Whilst most variables are not significant in LGDPP countries, only GDPP and EMR are not statistically significant in HGDPP countries, suggesting differences in the results for these two sub-sets of countries. The result that is puzzling is the significant effect of PGT on enrolment in HGDP countries and not in LGPP countries, whilst PGT is higher in LGP countries. This can be explained by the role of GDP in HGDPP countries given the fact that in pooled data, PGT has a significant effect on HEE. Briefly, these disaggregated results suggest that improved policy making is achieved if countries are analysed in smaller homogenous groups.

4.3 Inferences, Comparisons and Discussion of Findings

It is evident from the regression results that GDPP, PAG and Lxp depict a negative relationship with HEE among the SSA countries under investigation. This finding is against a priori expectation and relevant theories. For instance, the negative relationship between GDP per capita, life expectancy and HEE negates both consumption and investment theories; while the inverse relationship between PAG and HEE is opposed to the extant cohort size and sibling effects theory as postulated by Easterlin (1980). Apart from the negative relationship exhibited by these variables, of importance are GDP per capita and life expectancy as they do not appear to have long-run statistically significant impact on HEE. Although these conform to Gajderowicz’s (2014) findings in Poland, other studies such as Lauer (2000); Corazinni et al. (1972), and Connelly and Zhen (2003) found a positive relationship between GDP per capita and HEE. The reasons for these negative effects could be certain peculiar features exhibited by the SSA countries under investigation. The literature reviewed earlier illustrated that primary products such as agriculture and mining, and the service industry drive GDP in the SSA region. These sectors employ a larger portion of the working population in the region, with the likelihood that they can divert attention away from HEE. In the SSA economies, the drive for higher education is not due to favorable economic conditions. The a priori expectation is that a nation where a large proportion of citizens enjoys stable economic advantage stands the chance of sending enrollable youth to school, which is expected to increase HEE. However, this is empirically not the case in SSA both in the long-run and short-run analysis. It is noted that, in some developed economies where GDP per capita has been found to be a significant determining factor of HEE, governments have adopted proactive policies. It also appears that the colonial legacy and the World Bank's initial apathy towards higher education supported the notion that primary education is all that SSA requires to develop its agricultural sector. This has negatively affected higher education. However, the short-run lag variable of PAG, even though marginal, exhibits a positive relationship with HEE. This has important economic implications. The coefficient of both the lag and the current PAG shows a very weak relationship as the values are tending towards zero, meaning that the disparity between HEE and PAG is wide and its impact is felt very slowly. While the current PAG inversely impacts on HEE, the past PAG impacts positively.

A priori expectation is that high life expectancy among the SSA countries would impact positively on HEE, since people expect to live long to enjoy the return on education. Average life expectancy in SSA is 58.99 years. Apart from this figure being below the retirement age of most SSA countries, it is far below the 71 years' world average, with countries like Israel having life expectancy as high as 80.2 years in 2013. Low life expectancy could account for its lack of long-run significance on HEE. However, there is a short-run significant and positive relationship. The implication is that, an increase in life expectancy in a given population will improve social and economic welfare, thereby impacting positively on HEE. People that expect to live longer invest more in long term investments like higher education.

Again, the result indicates a positive and significant relationship between SSG, PGT and EMR which is not only supported by a priori expectation, but conforms to primary or sibling effects and secondary effects theory. The risk aversion hypothesis and population growth theory further validate this result. It is also consistent with the empirical findings of previous studies (Carla, 2004; Lauer, 2000; Easterlin, 1980; Gajderowicz et al., 2014; Vieira and Vieira, 2012). The implication for the region is that HEE is comparatively low, but could be increased through an increase in SSG if the dropout rate is adequately controlled as this will considerably influence HEE. A high level of failure in secondary school in the SSA region has reduced HEE considerably as the dropout rate is the highest in the world (Outlook, 2016). However, in the short run, the lag value of SSG significantly relates to HEE in an inverse direction in lag period one, but in a positive direction in lag period two. This implies that an increase in SSG in the immediate previous period reduces HEE in the present but increases HEE in the earlier period. This could be the reason why only 6% of HEE is absorbed from the SSG. As in the previous period, there are many secondary school graduates, with less enrolment in this period. It signifies that secondary school graduates are either absorbed into the labor market or are enrolled in higher education in the previous period, so that few of them apply in this period. In addition, the empirical result shows that, PGT in the region has long-run statistical significance. Viera and Vieira (2012) found that demographic factors such as birth rates, SSG, and employment rates were significant and positively related to HEE. However, the lag period two of population growth rate is statistically significant and it positively impacts on HEE in the past. This result has economic implications in that an increase in the past period of PGT brought about the current increase in the HEE but this increase could not be sustained over time as reflected in the widening gap between HEE and PAG. The findings from EMR shows that an increase in the EMR for the SSA region will induce enrolment rate in the short run. It appears that the nature of job offers to higher education graduates motivates enrolment among the enrollable population in the region in both the short and long run. As gains from employment are easily observable, its benefits can easily be linked to the few that access education in the region. This supports Vieira and Vieira's (2011) findings in Portugal. Glick and Sahn, (2000) and Sojkin (2012) also found employment rates to be positively related to HEE.

4.4 Panel Error Correction Model

Table 6: Error Correction Coefficient

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
Ect(-1)	-0.024	0.004	-6.172	0.000

Source: Authors' computation, 2018

The long- and short-run dynamics in the paper's present model are investigated using the Error Correction term (Ect). The Ect coefficient reveals how slowly or quickly the variables under investigation tend to revert to the equilibrium state (i.e., their speed of adjustment). As seen in the table above, the negative coefficient sign of the Ect indicates the previous existence of disequilibrium in the system, but the process of adjustment is in the right direction. The Ect value of -0.024202 (2.4%) suggests the speed of adjustment in the system from the short-run deviation to the long-run equilibrium and the tendency for improvement in HEE. Again, the Ect is found to be statistically significant at 1%, meaning that equilibrium in the long run is obtainable. This finding corroborates the finding of Rabbi (2011), which reveals that when Ect becomes strongly significant, it is evident that there is a stable, long-run relationship, and speed of convergence (steady-state) in the system is envisaged.

4.4 Summary, Discussion and Conclusion

This paper evaluated the relationship between HEE and the factors that determine it in 30 SSA countries using annual data for 1980-2015. The null hypothesis was that there is no significant statistical relationship between HEE and the factors that determine it in the SSA countries under investigation. The paper's contributions to knowledge include the fact that, to the best of the authors' knowledge, there are no existing studies on the determinants of HEE in SSA, although a few studies have been conducted on this issue in the OECD and other regions of the world, while studies also exist on individual countries within SSA. We provide evidence to support the conclusion that GDP per capita and life expectancy have no significant impact on HEE in the SSA region. We also provide evidence to establish that gains in the growing population age group have not been utilised to maximum benefit in SSA. Panel-ARDL was adopted in our estimating technique using augmented education Cobb Douglas as our model equation. Mixed relationships were found among the variables under investigation. Seven variables were selected from extant literature and they are within the context of the adopted theoretical framework. While SSG, EMR and PGT exhibit a significant positive long-run relationship, PAG, LXP and GDP per capita demonstrate a negative long-run relationship; whereas GDP per capita and life expectancy are not statistically significant. For short-run nexus, through the automatic lag selection procedure, lag two was found appropriate for the paper. All short-run variables are statistically significant except for PGT and GDP per capita, indicating that GDP per capita consistently exhibits no statistical significance in the short and long run. Again, while all short-run variables have a positive relationship with their lags, except lag one of SSG, Lxp and EMR, PAG and GDP per capita exhibit a negative relationship. The paper drew on insights from existing literature to adduce reasons for the various characteristics of variables and their peculiar features in relation to the SSA countries under investigation. The ECT result is significant and the coefficient is negatively signed; furthermore, the value that determines the speed of adjustment indicates 2.4% speed at which the system reverts to equilibrium. The study further classified all the SSA countries under investigation into high and low GDP per capita. As a robust check, analyses were conducted on countries with high GDP per capita (HGDPP) above $1000 and those with low GDP per capita (LGDPP) below $1000. GDP per capita failed to be statistically significant in all the analysis.

These findings suggest three main policy directions, namely, policy that will lead to birth control (demographic policy), policy that will enable PAG to access higher education (socio-economic policy) and orientation policy. It is recommended that the low 7% HEE rate in SSA should be addressed through the adoption of these policies. PAG, Lxp and GDP per capita that exhibit negative signs require urgent attention to revert the direction of the coefficients.

The quality of this paper could have been improved if variables such as expenditure or spending on education and parental education etc., had been included in our model; however, data on these variables, among others, is not available. This is thus one of the limitations of this paper.

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Appendices

Appendix A: Preliminary Estimation

Correlation Matrix

This section discusses the results from our correlation matrix on all the series as indicated in the table below.

Variables	HEE	EMR	LOGGDPP	Lxp	PAG	PGR	SSG
HEN	1.000000	-0.025016	0.049758	0.494798	0.136273	-0.167193	0.599199
EMR	-0.025016	1.000000	0.013006	0.011579	0.612099	0.207620	0.142342
LOGGDPP	0.049758	0.013006	1.000000	0.190810	0.014362	0.293288	0.072736
LXP	0.494798	0.011579	0.190810	1.000000	-0.034416	0.140214	0.450376
PAG	0.136273	0.612099	0.014362	-0.034416	1.000000	0.031226	0.017629
PGT	-0.167193	0.207620	0.293288	0.140214	0.031226	1.000000	0.004512
SOT	0.599199	0.142342	0.072736	0.450376	0.017629	0.004512	1.000000

Source: Authors' computation, 2018

The table indicates the correlation structure in the variables adopted in this panel model. This is an interesting result as it indicates that the variables under investigation have no multicollinearity problem.

Appendix B: Unit Root Result

To determine the form of the model to adopt, tests for stationarity of the variables in the data set were carried out. This was achieved by testing the unit root with three alternative methods proposed by the robust versions of Levin-Lin-Chu, Im-Pesaran-Shin and Augmented Dickey Fuller (Bornhorst and Baum, 2006).

Levin-Lin-Chu			Im-Pesaran-Shin		Augm. Dickey Fuller	
Variables	Order	P-Value	Order	P-Value	Order	P-Value
EMR	I(1)	0.0000***	I(1)	0.0000***	I(1)	0.0000***
HEE	I(1)	0.0000***	I(1)	0.0000***	I(1)	0.0000***
SSG	I(1)	0.0035***	I(1)	0.9999	I(0)	0.0050***
PGT	I(0)	0.0000***	I(0)	0.0000***	I(0)	0.0000***
PAG	I(1)	0.0001***	I(1)	0.0000***	I(1)	0.0000***
Log GDPP	I(0)	0.0000***	I(0)	0.0000***	I(0)	0.0000***
Lxp	I(0)	0.0000***	I(0)	0.0000***	I(0)	0.0000***

"***", "**" and "*" represent statistical significance at 1%, 5%, and 10%, respectively.

Source: Authors' computation, 2018

The paper tests for the presence of unit roots and identifies the order of integration for each variable in levels and first differences. The unit root test gives mixed results as some variables are stationary at levels while others are stationary at order one. These mixed results render P-ARDL the appropriate methodology because of its power to adequately incorporate I(1) and I(0) in the model, having met the assumption for the adoption of the technique requiring the dependent variables to be non-stationary at level.

Diagnostic Test

Overall, the result passes the required diagnostic test common to the panel ARDL model; the results are presented below:

Appendix C: RESULT ON CROSS SECTIONAL DEPENDENCE

Test	Statistics	Degree of Freedom	Prob. Value
Breusch-Pagan LM	5132.351	435	0.0000
Pesaran Scaled LM	159.2551	324	0.0000
Pesaran CD	3.642522	354	0.0003

Source: Authors' Computation, 2018

Test for Cross Sectional Dependence

In dealing with the problem of cross sectional dependence that might emerge from our data, the processes highlighted have been adopted. Since the P-Value of 0.003< 5%, the paper accepts the null hypothesis of no correlation of the residual and fails to accept the alternative hypothesis that there is correlation of the residuals in the model. This result is consistent with that of Kutu and Ngalawa (2016) on the test for cross sectional dependence.

Appendix D: RESULT ON WALD TEST

Test Statistic	Value	Df	Probability
F-statistic	4034.234	(9, 1057)	0.0000
Normalized Restriction (= 0)		Value	Std. Err.
Ssg		1.194102	0.029814
Pgt		-0.218077	0.030210
Pag		0.095496	0.006647
Lxp		-0.104968	0.010084
LogGdpp		0.017661	0.006814
Emr		0.003620	0.021036
Restrictions are linear in coefficients.			

Null Hypothesis: Ssg=Pgt=Pag=Lxp=LogGdpp=Emr=0

Source: Authors' Computation, 2018

Wald Test Results

The result shows the existence of a short-run relationship moving from the explanatory variables to the dependent variable at a P-value of 1%. It, therefore, indicates that we cannot accept the null hypothesis. We reject the null hypothesis and accept the alternative hypothesis.

Appendix E: DETERMINATION OF LAG SELECTION CRITERIA

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-34480.91	NA	7.04e+19	65.56637	65.59936	65.57887
1	-26499.59	15841.25	1.99e+13	50.48591	50.74986*	50.58598
2	-26367.60	260.2103	1.70e+13*	50.32814*	50.82304	50.51577*
3	-26327.90	77.74351	1.73e+13	50.34582	51.07167	50.62101
4	-26307.76	39.17398	1.83e+13	50.40068	51.35749	50.76344

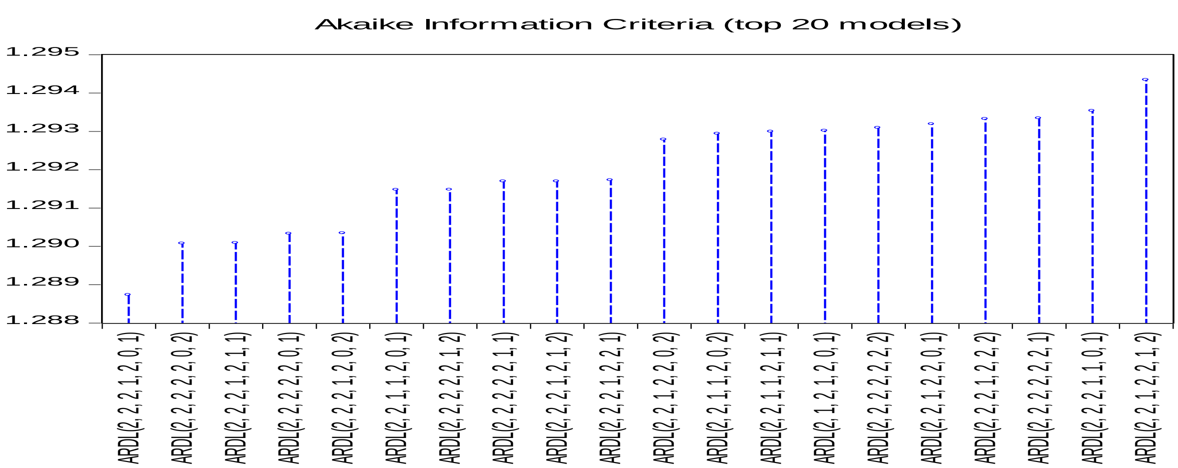
5	-26258.95	94.27292*	1.83e+13	50.40105	51.58881	50.85137
6	-26244.26	28.17927	1.95e+13	50.46627	51.88499	51.00416
7	-26213.89	57.85329	2.02e+13	50.50169	52.15137	51.12714
8	-26202.65	21.26967	2.17e+13	50.57347	52.45410	51.28648

Source: Authors' Computation, 2018

Panel ARDL Lag Determination

For the P-ARDL model, the regressions are estimated separately to obtain the optimal lag length for the variables under investigation. The orders of lags are selected using the Akaike Information Criterion (AIC), final prediction error (FPE), Hannan-Quinn information criterion, sequential modified LR test statistics (LR) and Schwarz Bayesian Criterion (SBC) which are used mostly in panel estimation. Based on the advantage of the P-ARDL model that different variables can be assigned different lags as they enter the model, this paper tests for various lags' lengths' selection criteria. The results reveal that lag 2 would be most preferred as indicated by FPE, AIC and HQ; thus, lag 2 was chosen for the method of estimation in P-ARDL which forms the optimal lag length in this paper.

Appendix F: Measuring the Strength of the P-ARDL Regression Model



Source: Authors' Computation

To establish the strength of the AIC model selection summary over other models (the Schwarz criterion and Hannan-Quinn criterion) as engaged in our P-ARDL regression model, and to further ascertain the short- and long-run relationships in our model, criteria graphs are employed to determine the top 20 P-ARDL models. From the existing model benchmark analysis, a lower value of AIC behaves better in any given model. It is clear from the figure that the first ARDL (2, 2, 2, 1, 2, 0,1) with a value of 1.288 in the model appears to be preferred over others as it offers the lowest value of the AIC.

Appendix G: Short-run result of SSA countries with low GDP per capita

COINTEQ01	-0.117547	0.059509	-1.975286	0.0518
D(TER(-1))	0.281577	0.152582	1.845406	0.0688
D(SOT)	-0.502720	0.481031	-1.045087	0.2992
D(SOT(-1))	0.172110	0.221785	0.776021	0.4401
D(PGT)	0.002296	0.019367	0.118557	0.9059
D(PGT(-1))	-0.008037	0.017681	-0.454555	0.6507
D(LOGPAG)	0.351494	0.336225	1.045412	0.2991
D(LOGPAG(-1))	0.337589	0.216317	1.560619	0.1227
D(LOGLXP)	13.24282	16.50874	0.802170	0.4249
D(LOGLXP(-1))	-11.28494	11.18056	-1.009336	0.3159
D(LOGGDPP)	0.000393	0.000310	1.267964	0.2086
D(LOGGDPP(-1))	0.000488	0.000252	1.939297	0.0561
D(EMP)	2.200928	2.052656	1.072234	0.2869
D(EMP(-1))	0.459408	0.490240	0.937107	0.3516
C	0.525698	0.310416	1.693530	0.0943

Appendix H: Demographic and socio-economic features of selected SSA countries for 2017

Country	Ag (0-14)	Age (15-24)	Age (0-24)	Pgt	Life xpt	GDP per capita	GDP Grt	Education expenditure
Burundi	45.61	19.75	65.36	3.26	60.5	$800	-0.50%	5.4
Benin	43.04	20.52	63.56	2.75	61.9	$2,200	4.60%	4.3
Botswana	32.4	21.32	53.72	1.19	54.5	$16,900	3.10%	9.6
Central R.	40.27	19.98	60.25	2.12	52.3	$700	5.20%	1.2
Cote d'Ivoire	37.54	20.93	58.47	1.88	58.7	$3,600	8%	4.7
Cameroon	42.6	19.55	62.15	2.58	58.7	$3,300	4.80%	3
DR Cong	42.2	21.44	63.64	2.42	57.3	$800	3.90%	2.2
Congo	41.53	17.26	58.79	2.06	59.3	$6,800	1.70%	6.2
Gabon	41.98	20.37	62.35	1.92	52.1	$19,300	3.20%	2.7

Ghana	38.2	18.66	56.86	2.18	66.6	$4,400	3.30%	6.2
Gambia	37.88	20.64	58.52	2.11	64.9	$1,700	2.30%	2.8
Kenya	40.87	18.83	59.7	1.81	64	$3,400	6%	5.3
Liber	42.3	18.9	61.2	2.44	59	$900	2%	2.8
Lesotho	32.4	19.56	51.96	0.3	53	$3,100	2.40%	13
Mali	47.27	19.19	66.46	2.96	55.8	$2,300	5.30%	3.6
Mozam	44.92	21.51	66.43	2.45	53.3	$1,200	4.50%	6.5
Mauritan	38.87	19.86	58.73	2.2	63	$4,400	3.20%	2.9
Mauritius	20.44	15.06	35.5	0.61	75.6	$20,500	3.50%	5
Malawi	46.53	20.49	67.02	3.32	61.2	$1,100	2.70%	5.6
Namibia	32.39	20.35	52.74	1.98	63.6	$11,800	4.20%	8.3
Niger	49.31	18.85	68.16	3.22	55.5	$1,100	5.20%	6.7
Rwanda	41.53	18.87	60.4	2.53	60.1	$1,900	6%	5
Senegal	41.85	20.36	62.21	2.42	61.7	$2,600	6.60%	7.2
Sierr Lo	41.9	22.19	64.09	1.1	51.6	$1,700	4.30%	2.7
Swaz	35.5	22.19	57.69	1.1	51.6	$9,800	0.50%	7.1
Togo	40.44	19.34	59.78	2.66	65	$1,500	5.30%	5.3
Uganda	48.26	21.13	69.39	3.22	55.4	$2,100	4.90%	1.7
South A.	28.34	18.07	46.41	0.99	63.1	$13,200	0.10%	6.1
Zambia	46.08	20	66.08	2.94	52.5	$3,900	3%	1.1
Zimba	37.8	21.29	59.09	2.2	58	$2,000	-0.30%	8.4
Avg total	40.008	19.882	59.890	2.164	58.99	4713.3	0.036	5.0867