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# Revisiting the human capital-led growth hypothesis in Sub-Sahara Africa (SSA): The economic complexity perspective

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**Abstract**
This study employs panel data from Sub-Saharan Africa between 1990 to 2022. The source of the data is the World Bank Development Indicator (WDI) data base. The idea that a country's growth is driven by human capital and the role of economic complexity that reflects a country's production capabilities is examined. The dynamic panel model estimators such as difference Generalised Method of Moments (GMM) and system GMM is adopted and discovers that the economic complexity dynamics in sub-Saharan Africa (SSA) do not have a significant impact on the region's growth. This means that, despite the idea that economic complexity leads to better knowledge and the ability to produce a variety of sophisticated products, it is actually a traditional measure of human capital, such as average years of schooling, which are more important for growth in SSA. That said, our results suggest that economic complexity can enhance the impact of both human and physical capital on growth. A framework that promotes the judicious combination of both human capital and physical capital as two forms of productivity enhancement to accelerate the economic growth process in the SSA is hereby recommended. This research further recommends the removal of bottlenecks in infrastructural development by paying more attention to factors such as economic complexity and institutional quality that are capable of fostering the development of both human and physical capital.
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## 1. Introduction

Based on the widespread assertion that the causal factors responsible for the impressive performance of the economies of most developed countries are their impressive commitment to human capital formation, African economies have continued to attach importance to human capital in their growth process in their pursuit of inclusive and sustainable economic growth. However, despite high returns on education, the sub-Saharan Africa (SSA) region has a predominantly weak human capital base. Compared to developed and emerging economies, the available educational and training institutions in Africa are characterized by inadequate teachers and trainers and the necessary tools and equipment for effective teaching and training to build a productive human capital base. The quality of education and training offered in Africa is also compromised, as teachers and available teaching tools tend to be overstretched by the high number of pupils and students. Although the implementation of poverty reduction strategy programs (PRSPs) has resulted in some expansion of human capital investment in Africa in recent years, the rate of expansion has remained low in comparison to some East Asian countries such as Malaysia and South Korea (Baah-Boateng, 2013). This latter position supports the view that a nation may have high school enrolment, yet characterized by low quality of education. Hence, one year of schooling in many African countries is not synonymous with that in developed countries.

 

Thus, the relatively impressive growth process of developed economies compared to that of developing economies has further triggered the assertion that differences in growth performance across nations are not so much about natural resources or the endowment and stock of physical capital, but the quality and quantity of human resources. Therefore, it is imperative to identify the fundamentals with the potential to enhance the quality of human capital formation and its impact on growth in Africa. This study revisits the human capital-led growth hypothesis to identify how economic complexity can aid human capital development and spur economic growth in Africa. Economic complexity reflects a high degree of knowledge accumulation and encourages the development of highly skilled workers who can obtain higher incomes (see Hoeriyah et al., 2022). More complex economies have better institutions, more educated workers, and more competitive environments (Sepehrdoust et al., 2019). Generally, the concept of economic complexity in a country refers to the production of domestically based knowledge products and the diversification of export goods by the country. This implies the intense application of technical knowledge in product diversification to encompass it in domestic consumer markets on the one hand and foreign markets on the other (Utkovsklbi et al., 2018).

However, while several existing studies have separately investigated the human capital-led growth nexus (see Anyanwu et al., 2015; Asongu & Odhiambo, 2020; Wirajing et al., 2023), and economic complexity and growth nexus (Hausmann et al., 2011; Ourens, 2013; Bastos & Wang, 2015; Zhu & Li, 2016; Demiral 2016; Stojkoski & Kocarev, 2017; Hoeriyah et al., 2022), to the best of my knowledge, none has considered the possibility of a complementary effect of human capital formation and economic complexity on economic growth. To bridge this gap, we extend the literature on knowledge-led growth beyond analyzing the effects of human capital and economic complexity on growth. Instead, we hypothesized that their complementary effects would benefit growth. In addition to determining the relative effects of the traditional measure of human capital, such as the average year of schooling and economic complexity on economic growth, the study also show results that give credence to the complementary effect of human capital and economic complexity on growth in SSA.

From a methodological point of view, the empirical analysis of growth models often relies on cross-sectional data, with the underlying assumptions being comparable production functions and convergence parameters based on similar technical progress across countries. However, as joint technological advancement has not been witnessed even within so-called homogeneous regions, the quality of institutions, degree of economic complexity, and human capital formation are predicted to vary among African countries. To account for such heterogeneity, the approach would have been to appropriately estimate single-country regressions. However, while such single-country estimates can capture a variety of individual-country structures, they neglect certain essential information in a regional structure. This comprises, for example, a typical geographical topography, similar governance structure, similarities in economic development level, and other cultural and economic indicators. To capture these commonalities, particularly in developing and populous regions such as SSA, we prefer a dynamic panel data modeling technique that accommodates both the commonalities and heterogeneity dynamics of the variables of interest, unlike conventional panel models.

 

Base on the foregoing, the remainder of this paper is structured as follows: chapter two reviews various relevant literature, chapter three considers the methodology, chapter four explains the results and the findings while chapter five concludes the paper with some recommendations.

**2.0 Literature Review**

Miyanda and Venkatesh (2017) analyzed the effect of human capital on the Zambian economy by employing the VECM model for analysis. The result of the study showed that the human capital variables of education and healthcare significantly positively impact economic growth. Further, it was discovered that health's impact was higher than education. Kowal and Paliwoda-Pkosz (2017) found that human capital in emerging economies enhances the level of economic growth. Similarly, Ogundari and Awokuse (2018) determine the effect of human capital on economic growth in Sub-Saharan Africa, covering 35 countries from 1980 to 2008. The authors employ health and education as indicators of human capital. The empirical results show that the two measures of human capital positively affect the level of economic development in Sub-Saharan Africa. Matousek and Tzeremes (2019) re-examine the effects of human capital on countries economic growth using a sample of 100 countries over the period from 1970 to 2014. The empirical findings suggest that the effects of human capital on countries' economic growth levels are positive and significant.

In their study, Adeyemi and Ogunsola (2019) analyzed the effect of human capital development on the economic growth of the Nigerian economy by utilizing time-series data spanning 1980 to 2013. The study used the ARDL model to assess the relationship between the variables investigated. The findings of the study showed the absence of a significant impact on economic growth by human capital

Parika and Singh (2020) conducted a study to examine the relationship between human capital and economic growth in India. The study utilizes annual time series data for the period 1980–2017. The study's major findings suggest that human and physical capital are the major determinants of economic growth. Employing both the health and education dimensions of human capital, Intisar et al. (2020) conducted a study in two selected geographically distributed regions, encompassing 19 Asian countries, to assess the impact of human capital on economic growth. Chekina and Vorhach (2020) studied the effect of education on the level of economic development over the periods 2015–2019 in the Eurozone and found that there is an increasing trend with higher expenditure on education corresponding to higher population qualification and a larger size of GDP. The results further reveal that there is no strong dependence the population’s skills upgrading on GDP growth.

Similarly, Hanushek and Woessmann (2020) demonstrated in their study conducted on knowledge and economic growth that human capital development positively affects economic development. Their findings reveal that human capital has a significant and statistically positive relationship with economic growth in southern Asia. The authors reveal that human capital and economic growth have unidirectional causality in both regions.

Adeleye et al. (2022) studied human capital and economic growth dynamics in the Middle East and North African countries. The study adopted two human capital indicators, education enrollment and life expectancy at birth, based on unbalanced panel data from 19 MENA countries covering the period 1980–2020. The findings reveal that both human capital indicators influence economic growth positively. Further examination of the findings reveals that primary education exerts the same significance as other education indicators, while life expectancy appears to be the most potent human capital indicator. Saldanha et al. (2022) found that human capital and market intensity positively moderate the influence of growth using cross-sectional primary data from a sample of 186 U.S. credit unions.

On their part, Wang et al. (2022) conducted a study to investigate the effect of life expectancy on economic growth in the six WHO regions in 134 countries. The results illustrated the heterogeneity of spatiotemporal trends in life expectancy. The results indicate that Africa and Southeast Asia show much lower life expectancy levels than the Americas, Europe, and Western Pacific, which exhibit relatively higher life expectancy levels. The findings further reveal that countries with low overall l life expectancy levels show a relatively more robust upward trend in GDP per capita than the overall upward trend and vice versa. Chowdhury (2022) supported his study conducted using quarterly data from 1974 to 2019 to analyze the effect of the internationalization of education on the level of economic development in Australia that there is a long-run positive relationship and a short-run dynamic effect of education on the economic development of Australia. The findings of Chowdhury (2022) are similar to those of Prasetyo and Kistanti (2020), who also found out that education contributes to economic development.

Akpoghelie (2023) adopts an Autoregressive Distributed Lag (ARDL) bounds testing approach to scrutinize the long-run and short-run dynamics between human capital development (encompassing education, health, and government expenditure) and economic growth in Nigeria. The study unveils a robust and positive relationship between human capital and economic growth, underscoring the multifaceted contributions of education, health, and government investment to Nigeria's economic development. Olabode & Adebiyi (2023) take a distinctive approach by disaggregating Nigeria's economy into sectors and examining the impact of human capital on each sector's growth. Their findings reveal that human capital exerts a more potent influence on the growth of the service and industrial sectors compared to the agricultural sector. This sectoral differentiation enhances our understanding of the heterogeneous effects of human capital across diverse economic activities.

Gyamfi-Yeboah & Asiamah (2023) delve into the impact of human capital, encompassing education and health, on inclusive economic growth in Ghana, with a keen focus on poverty and income inequality. Their findings reveal a positive and significant relationship between human capital and economic growth, yet they underscore the imperative of targeted interventions to ensure that the benefits of growth are inclusive. This study emphasizes the nuanced relationship between human capital and inclusive development, offering insights for policymakers seeking comprehensive growth strategies.

 

## 3.0 Methodology

### 3.1Model specification

The augmented Solow growth model is the theoretical foundation upon which the human capital–led growth hypothesis is examined. The augmented Solow growth model is an improvement over the standard Solow growth model because it accounts for the role of human capital, which has not been explicitly captured previously. According to Mankiw et al. (1992), the motivation for including human capital in the augmented Solow model is the non-homogeneity of labor in the production process, either within a nation or across different economies, given their different education and skills. Following Mankiw et al. (1992), the augmented growth model with three reproducible factors was as follows:

$$Y_{it} = A_{it} K_{it}^{\alpha_1} H_{it}^{\alpha_2} L_{it}^{\alpha_3} \tag{1}$$

where $Y_{it}$ is output, $A_{it}$ is the level of technology that augments physical capital $K_{it}$, human capital $H_{it}$, and labor $L_{it}$. Equation (1) is our baseline production function with the standard assumption of a constant return-to-scale $(\alpha_1 + \alpha_2 + \alpha_3 = 1)$. Dividing equation (1) through L enables us to further express the production function equation in per worker terms as follows:

$$y_{it} = A_{it} h_{it}^{\alpha_1} k_{it}^{\alpha_2} \tag{2}$$

Despite the transformation of the baseline production function such that it is expressed in per worker terms, it is instructive that equation (2) is only assumed to have implicitly captured an underlying set of economic complexities. However, innovation in the context of this study explicitly determines how economic complexity affects output through its complementary effect on human capital development. As a result, we will be specifying the technology parameter as:

$$A = A_0 h_{it}^{\beta_1 \left(x - x^*\right)} k_{it}^{\beta_2 \left(x - x^*\right)} \tag{3}$$

where $A_0$ measures the basic level of technology and $x^*$ represents economic complexity. While $x$ is the current level of economic complexity in a country, $x^* - x$ on the other hand denotes the degree which economic complexity falls short of ideal conditions. For instance, when $x^* = x$, the model reduces to its standard form in the previous literature. Substituting equation (3) into equation (2) yields the following:

$$y_{it} = A_0 h_{it}^{\beta_1 \left(x - x^*\right)} k_{it}^{\beta_2 \left(x - x^*\right)} h_{it}^{\alpha_1} k_{it}^{\alpha_2} \tag{4}$$

For convenience, equation (4) can be further rearranged as follows.

$$y_{it} = A_0 h_{it}^{\alpha_1 + \beta_1 \left(x - x^*\right)} k_{it}^{\alpha_1 + \beta_2 \left(x - x^*\right)} \tag{5}$$

Taking the natural log of the rearranged equation would yield the following.

$$\ln y_{it} = \ln A_0 + \left[\alpha_1 + \beta_1\left(x - x^*\right)\right] \ln h_{it} + \left[\alpha_2 + \beta_2\left(x - x^*\right)\right] \ln k_t \tag{6}$$

Following Pritchett's (2001) approach, this study focuses on explaining the growth of output per worker through the growth of human and physical capital per worker. Thus, we take the differences in these variables of interest to arrive at the following:

$$\hat{y}_{it} = \hat{A}_0 + \left[\alpha_1 + \beta_1\left(x - x^*\right)\right] \hat{h}_{it} + \left[\alpha_2 + \beta_2\left(x - x^*\right)\right] \hat{k}_t \tag{7}$$

To rewrite the theoretical model in equation (7) in an estimable form, we first simplify the specification, as shown below.

$$\hat{y}_{it} = \hat{A}_0 + \left(\alpha_1 + \beta_1 x^*\right) \hat{h}_{it} + \beta_1 x \hat{h}_t + \left(\alpha_2 + \beta_2 x^*\right) \hat{k}_{it} + \beta_2 x \hat{k}_t \tag{8}$$

We simplify further, such that $\delta = \left(\alpha_1 + \beta_1 x^*\right)$, $\alpha_0 = \hat{A}_{it}$, and then add the stochastic terms (error term) to arrive at our estimable empirical model, as follows:

$$\hat{y}_{it} = \alpha_0 + \delta_1 \hat{h}_{it} + \beta_1 x \hat{h}_{it} + \delta_2 \hat{k}_{it} + \beta_2 x \hat{k}_{it} + \varepsilon_{it} \tag{9}$$

Equation (9) is our empirical model in the whole form, where output growth ( $y_{it}$ ) is expressed as a function of human capital ($h_{it}$), physical capital ($k_{it}$), and the indirect effect of economic complexity through both human and physical capital. The term $x$ captures the effect of economic complexity (eco), as shown in equation (10).

$$\hat{y}_{it} = \alpha_0 + \alpha_1 \hat{h}_{it} + \alpha_2 \hat{k}_{it} + \alpha_3 eco_{it} + \alpha_4 z'_{it} + \varepsilon_{it} \tag{10}$$

The empirical model in equation (10) is used to determine the relationship between the concept of human capital (h) and economic complexity (eco), which matters most for accelerating the growth process. While this is in line with the main objective of this study, the Z term in the specification is a vector representing the control variables, namely, inflation and exchange rate.

To determine whether the effects of economic complexity on growth would be felt more through human capital and by extension, physical capital, we further extended the model in equation (10) to include an interaction term.

$$\begin{aligned}\hat{y}_{it} = {} & \alpha_0 + \alpha_1 \hat{h}_{it} + \alpha_1 \hat{k}_{it} + \alpha_2 eco_{it} + \alpha_3\left(h_{it} * eco_{it}\right) + \alpha_4\left(k_{it} * eco_{it}\right) + \\ & \alpha_5 \inf_{it} + \alpha_6 exr_{it} + \varepsilon_{it}\end{aligned} \tag{11}$$

The parameters of interest in equation (11) are $\alpha_3$, and $\alpha_4$ which captures the interaction effects of economic complexity through human capital and physical capital, respectively. Irrespective of the alternative economic growth regressions under consideration, we expect both human and physical capital to impact economic growth positively. We also predict economic complexity to impact economic growth positively, both directly and indirectly, through human and physical capital. However, while we expect increasing inflation to adversely affect economic growth, the impact of the exchange rate on economic growth is somewhat ambiguous, depending on whether the exchange rate is appreciating or depreciating.

### 3.2 Data and Description of variables

The variables of interest in this study were chosen based on their theoretical relevance and use in the empirical literature. The data are from a balanced panel of 32 Sub-Saharan African (SSA) countries covering the period between 1990 and 2022, at an annual frequency. The choice of sample coverage and selected countries was mainly based on data availability. Economic growth is proxied by GDP per capita, which is the sum of the country's monetary value of goods and services divided by the midyear population. The adoption of GDP per capita as an indicator of economic growth is inspired by the studies of Asongu and Odhiambo (2020), Intisar et al. (2020), and Prasetyo and Kistanti (2020). Human capital is measured using the average years of schooling, which considers the typical duration required to complete each education level. Economic complexity is an index based on Hausmann et al. (2014). The economic complexity index ranks countries based on the diversity (the number of different types of goods that can be produced within a country) and ubiquity (the number of nations that can produce a specific type of good) of their exports to determine the level of productive knowledge that each nation has access to. Consequently, nations at the higher end of the economic complexity index have advanced manufacturing capabilities because they can export a wider variety of technologically advanced goods. In addition to these variables of interest, we control for physical capital, inflation, and exchange rates. Physical capital is measured as the log of the first difference in gross fixed capital formation, formerly known as gross domestic fixed investment. The log of the first difference of the consumer price index (CPI) is used as a proxy for the inflation rate.

In contrast, the log of the first difference of the national currency of the investigated African economies relative to the US dollar is the measure of the exchange rate. Economic growth, physical capital, inflation, and exchange rate data were obtained from the World Development Indicator (WDI) online database for 2023. However, data for human capital are sourced from Penn World Table version 10.0, while the economic complexity index was obtained from MIT's observatory of economic complexity.

### 3.3 Estimation technique

The human capital-led growth regressions in equations (10) and (11) can be estimated using any of the standard panel model estimators, such as the pooled ordinary least squares estimator (Pooled OLS), Fixed Effects and Random Effects. However, the Pooled OLS is said to be highly restrictive, given the heterogeneity consequence of its assumption of a common intercept and slope coefficient for all cross-sections. For the fixed effect, the estimator assumes common slopes but variant country-specific intercepts and therefore tends to suffer from the loss of degrees of freedom (see Baltagi, 2008). In contrast to the fixed effects model, the random effects model, on the other hand, is regarded as less problematic in terms of degrees of freedom because it assumes common intercepts. Notwithstanding this, the random effects assumption of no time variability is considered unrealistic because it implies that the error at any period is uncorrelated with past, present, and future errors (see Arellano, 2003; Loayza and Ranciere, 2002).

More importantly, none of the aforementioned static approaches to modelling panel data has the potential to capture the dynamic nature of the data, as they can only deal with structural heterogeneity, particularly in the form of random or fixed effects, while imposing homogenous slope coefficients across countries, even though there may be substantial variations between them (see Samargandi et al., 2014). However, the Generalized Method of Moments (GMM) estimator is intended for scenarios with few periods, and many individuals permit some of the OLS assumptions to be relaxed. Even in the presence of endogenous right-hand-side variables, the estimator corrects for endogeneity in the lagged dependent variable and delivers consistent parameter estimates. Individual fixed effects, heteroskedasticity, and autocorrelation within individuals are also supported (Roodman, 2009). As presented by Arellano and Bond (1991), the initial stage of this estimation approach is to eliminate unobservable heterogeneity ($\mu_i$) by first differencing the specified equations of interest. For example, in a generic version, human capita-led growth can be reformulated, as shown below, to allow the GMM estimation technique to be used.

$$\begin{aligned}\Delta y_{i,t} - \Delta y_{i,t-1} = {} & (\beta_1 - 1)\left(y_{i,t-1} - y_{VOL_{i,t-2}}\right) + \beta_2\left(h_{i,t} - h_{i,t-1}\right) + \beta_3\left(k_{i,t} - k_{i,t-1}\right) + \beta_4\left(eco_{i,t} - eco_{i,t-1}\right) + \\ & Z'\left(\gamma_{i,t} - \gamma_{i,t-1}\right) + \left(\varepsilon_{i,t} - \varepsilon_{i,t-1}\right)\end{aligned} \tag{12}$$

For example, Equation (12) is a typical method of connecting changes in economic growth to changes in human capital, physical capital, economic complexity (eco), and control variables (Z). There is still a correlation between the errors and lagged dependent variable in the differenced equation, which must be rectified by instrumentation. Endogenous problems are addressed in the absence of exogenous factors that can supply external instruments by developing internal instruments following Arellano and Bover (1995) and Blundell and Bond (1998). The Arellano-Bover/Blundell-Bond estimator extends Arellano-Bond by assuming that the first differences of instrument variables are uncorrelated with the fixed effects. It creates a GMM system by combining two equations: the original in levels and the converted in differences. This enables the introduction of more instruments and can increase the efficiency. Instruments for the differenced equation are acquired from the lagged levels of the explanatory variables, whereas instruments for the level equation are acquired from the lagged differences of the explanatory variables.

The GMM estimator's consistency depends on the correctness of the moment conditions, which can be checked using two specification tests: the Arellano-Bond test for autocorrelation checks for no second-order serial correlation in the disturbances. The second test, Hansen's (1982) J-test of over-identifying limitations, was used to validate the instrument's validity. The Hansen test's joint null hypothesis is that the instruments are exogenous (i.e., uncorrelated with the error term) and that the excluded instruments are omitted from the estimated equation. Because of its consistency in autocorrelation and heteroskedasticity, the Hansen test is used instead of the Sargan (1958) test of over-identifying limitations (Roodman, 2009).

## 4.0 Empirical Results

This study revisits the human capital-led growth hypothesis in the context of sub-Saharan African countries. The innovations in this study include, among others, the complementary effect of economic complexity in enhancing the impact of human capital on economic growth. The analysis of the variables is given below:

### 4.1 Preliminary results

Table 1 presents the basic summary statistics for each variable. The statistics of interest, represented in the table, are the mean, minimum, maximum, and standard deviation (Std. Dev.) statistics. The mean statistic shows that the average GDP per capita (GDPC) expressed in constant USD is 2198.8, for the period under consideration and in the context of the 17 SSA countries considered in this study. However, the maximum GDP per capita recorded over the same period covered, and for the selected SSA countries is 10643, while the minimum statistic shows that the region's most negligible GDP per capita is 334. It is not surprising that the standard deviation statistic for GDP per capita is as large as 2327.8, given that the statistics measure the degree of dispersion between the maximum and minimum statistics. Concerning the human capital variable, the table shows that the average number of years of schooling is five in the selected SSA. For the physical capital variable, measured as the percentage share of gross fixed capital formation in GDP, the mean statistics show that it is 22% of the GDP on average, while the maximum recorded is 81%, and the least is 2%. Compared to the rest of the world, the fact that the mean statistic reported for the economic complexity index (ECI) in the table is negative indicates that the region has a lower economic complexity than a region with a positive ECT. It is instructive, however, that there is no significance to the value of the ECI itself, other than for the sake of comparison. Notwithstanding, an improvement in the ECI is expected to enhance human capital development and, by extension, economic growth.

**Table 1: Summary Statistics**

| | GDPC | PCAP | HCAP | ECI | CPI | EXR |
|---|---|---|---|---|---|---|
| **Mean** | 2198.84 | 22.24 | 5.14 | -0.95 | 104.38 | 543.89 |
| **Maximum** | 10643.77 | 81.02 | 11.37 | 0.37 | 679.89 | 4096.12 |
| **Minimum** | 334.02 | 2.10 | 0.56 | -2.34 | 0.03 | 0.13 |
| **Std. Dev.** | 2327.80 | 8.60 | 2.34 | 0.57 | 68.81 | 775.19 |
| **Observations** | 459 | 459 | 459 | 459 | 459 | 459 |

Table 2 presents the correlation coefficients, and the goal was to test the strength of the degree of relationship between and among the variables of interest. The table shows no statistically significant correlation between physical capital and GDP per capita. However, we find a 60% correlation between GDP per capita and human capital that is statistically significant at the 1% significance level. This finding of a strong correlation between human GDP per capita is not only supported by Ding et al. (2021). This, among other things, further fuels our concern about which matters most: human capital and physical capital, as channels for enhancing the impact of economic complexity and institutional quality on GDP per capita. The table also shows a significant correlation between the GDP per capita and economic complexity.

**Table 2: Correlation Coefficients**

| | GDPC | PCAP | HCAP | ECI | CPI | EXR |
|---|---|---|---|---|---|---|
| **GDPC** | 1 | | | | | |
| **PCAP** | 0.0571<br>(0.2225) | 1 | | | | |
| **HCAP** | 0.6728***<br>(0.0000) | -0.0517<br>(0.2693) | 1 | | | |
| **ECI** | 0.1947***<br>(0.0000) | -0.3113***<br>(0.0000) | 0.1855***<br>(0.0001) | 1 | | |
| **CPI** | 0.0671***<br>(0.1512) | 0.0227<br>(0.6267) | 0.2428***<br>(0.0000) | 0.0905**<br>(0.0526) | 1 | |
| **EXR** | -0.2039***<br>(0.0000) | -0.0125<br>(0.7892) | -0.0565<br>(0.2267) | 0.0735<br>(0.1158) | 0.0929<br>(0.0467) | 1 |

Although the regression coefficients reported in Table 3 were obtained from both the static and dynamic panel data models, the discussion of the findings is mainly based on the estimates obtained from the best fit of the different variants of the panel data models. The probability value associated with the Hausman test was significantly less than 0.05, indicating the rejection of the null hypothesis. This suggests that the fixed effect (FE) model is most appropriate in terms of the static panel model. However, this study cannot depend on the FE estimator to offer robust remarks on the nexus between economic growth and human capital because the FE has some weaknesses, as it does not address the problems of endogeneity, unobserved heterogeneity, and simultaneity bias (Samargandi et al., 2014). To overcome these challenges, we go beyond the FE estimator of the static panel model and consider estimates based on dynamic panel model estimators, such as difference GMM and system GMM. To determine the accuracy of the estimated dynamic panel data models, the AR(2) and Hassen-J tests are typically employed. In the former case, the null hypothesis is that the errors in the first-difference regression exhibit no second-order serial correlation (AR(2)). For the Sargan-Hassen test, the joint null hypothesis is that the instruments are valid and uncorrelated with the error term. Overall, both the AR(2) and Hasse-J tests are applied to the difference GMM (diff-GMM) and system GMM (sys-GMM), with the option of one step (1) and two steps (2) in both cases.

Irrespective of whether the estimated dynamics panel model is a different GMM or system GMM, the probability values reported in square brackets are large, implying the non-rejection of the null hypothesis of no second-order serial correlation and the validity of the instruments, respectively. In other words, the GMM findings presented in Table 4.5 are well estimated, given that the AR (2) and Hassen probability tests are all greater than 10%. The only exception is when the estimated system GMM is a two-step option in which the null hypothesis of no second-order serial correlation is rejected. Regarding the overall fit of the models, the probability values appear to be more significant for the difference GMM in two steps; hence, the empirical findings are discussed based on the empirical estimates obtained from the diff-GMM (2) model.

The coefficient on GDP per capita growth lag is both positive and statistically significant, thus confirming the importance of accounting for the dynamic nature of economic growth data. This finding is supported by Wirajing et al. (2023), who also used the GMM estimator to model and revisit Africa's human capital-economic growth nexus. Regarding the question of which matters most between traditional human capital development and economic complexity in explaining the growth process in Africa, we find the coefficients on both indicators to be positive. However, the significance of this impact appears to be statistically viable, mainly in the case of traditional human capital (HCAP) development. This result indicates that economic growth measured by GDP per capita in Africa is significantly ameliorated by growth in human capital, which is supported by several previous studies (see Soukiazis and Antunes, 2012; Intisar et al., 2020; Ofori & Asongu, 2021; Wirajingetal.,2023).

Moving on to the complementary effect of economic complexity on growth through the human capital channel, the coefficient of interest in Table 4, denoted as HCAP × ECI, captures the interaction between human capital and economic complexity. Interestingly, the coefficient of the interactive terms is positive and statistically significant not only through human capital channels, but also through the physical capital channel. This suggests that, while the degree of economic complexity in SSA might be too low to directly affect the growth process significantly, it tends to complement the significant effect of both humane capital and physical capital on growth. That said, it is instructive that the degree of the commentary effect of economic complexity on growth is in terms of magnitude higher when the channel of transmission of the effect of economic complexity is through human capital than physical capital.

**Table 3: Regression result without interaction term**

| | (1) OLS | (2) FE | (3) RE | (4) Diff-GMM-(1) | (5) Diff-GMM-(2) | (6) Sys-GMM-(1) | (7) Sys-GMM-(2) |
|---|---|---|---|---|---|---|---|
| ***Dependent variable: GDP per capital growth*** | | | | | | | |
| *Constant* | 0.0380*** (0.0108) | 0.0163 (0.0176) | 0.0357*** (0.0114) | | | 0.0458* (0.0271) | 0.0578* (0.0324) |
| *LGDPC(-1)* | | | | 0.0401** (0.0141) | 0.1202** (0.0412) | 0.153** (0.0746) | 0.1630*** (0.0070) |
| *PCAP* | 0.0004* (0.0002) | 0.0002 (0.0003) | 0.0003 (0.0002) | 0.0014*** (0.0004) | 0.0015*** (0.0005) | 0.0007** (0.0003) | 0.0008** (0.0004) |
| *HCAP* | 0.0026*** (0.0007) | 0.0117*** (0.0025) | 0.0030*** (0.0009) | 0.0200*** (0.0065) | 0.0178** (0.0073) | 0.0023*** (0.0070) | 0.0024*** (0.0009) |
| *ECI* | 0.0011 (0.0033) | 0.0198*** (0.0064) | 0.0004 (0.0038) | 0.0024 (0.0092) | 0.0036 (0.0076) | 0.0018 (0.0030) | 0.0005 (0.0044) |
| *INFL* | 0.0031 (0.0022) | -0.0002 (0.0060) | 0.0031 (0.0023) | 0.0211** (0.0093) | 0.0197 (0.0147) | 0.0014 (0.0049) | 0.0002 (0.0067) |
| *EXR* | 0.0380*** (0.0108) | 0.0163 (0.0176) | 0.0357*** (0.0114) | -0.0105 (0.0113) | -0.0120 (0.0143) | -0.0034*** (0.0020) | -0.0038*** (0.0013) |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| *Hausman test* | | 45.18 [0.0000] | | Not applicable (N/A) | | | |
| *AR(1)* | Not applicable (N/A) | | | -3.26[0.001] | -2.89[0.004] | 3.42 [0.010] | -2.86[0.004] |
| *AR(2)* | | | | 1.31[0.191] | 0.92[0.360] | 2.59[0.101] | 1.85[0.064] |
| *Hansen J-test* | | | | 14.52 [0.630] | 13.39[0.768] | 8.75[0.119] | 8.75[0.119] |
| *Countries* | 17 | 17 | 17 | 17 | 17 | 17 | 17 |
| *Observation* | 442 | 442 | 442 | 408 | 425 | 425 | 425 |

Note: Values in parentheses are standard errors and p-values for those in the square parentheses, while *** p<0.01, ** p<0.05, and * p<0.1 denotes 1%, 5%, and 10% levels of significance.

**Table 4: Regression result with interaction term**

| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** |
|---|---|---|---|---|---|---|---|
| | **OLS** | **FE** | **RE** | **Diff-GMM-(1)** | **Diff-GMM-(2)** | **Sys-GMM-(1)** | **Sys-GMM-(2)** |
| ***Dependent variable: GDP per capital growth*** | | | | | | | |
| *Constant* | 0.0404* (0.0238) | 0.0687* (0.0353) | 0.0382 (0.0256) | | | -0.0386 (0.8530) | -0.4270 (0.7860) |
| *LGDPC(-1)* | | | | 0.1050 (0.0791) | 0.1430 (0.5310) | 0.0941 (0.1430) | -0.0028 (0.0982) |
| *PCAP* | 0.0005** (0.0002) | 0.0003 (0.0003) | 0.0003 (0.0002) | 0.0009** (0.0005) | 0.0410*** (0.0011) | 0.0181** (0.0017) | 0.0008 (0.0016) |
| *HCAP* | 0.0079* (0.0041) | 0.0246*** (0.0070) | 0.0092** (0.0045) | 0.0315*** (0.0068) | 0.0898*** (0.0211) | 0.1798*** (0.0310) | 0.1120*** (0.0020) |
| *ECI* | 0.0624* (0.0115) | 0.0183* (0.0062) | 0.0166* (0.0025) | 0.0434* (0.0193) | 0.2246** (0.0480) | 0.5430*** (0.0880) | 0.4251*** (0.0690) |
| *INFL* | 0.0031 (0.0023) | 0.0019 (0.0061) | 0.0030 (0.0024) | 0.0277*** (0.0105) | 0.0206 (0.0321) | -0.0370 (0.0478) | -0.0206 (0.0426) |
| *EXR* | - 0.0025*** (0.0010) | 0.0042 (0.0060) | -0.0021* (0.0012) | -0.0162 (0.0123) | -8.79e-05 (0.0291) | -0.0050 (0.0141) | -0.0092 (0.0132) |
| *HCAP*ECI* | 0.0020*** (0.0004) | 0.0063* (0.0033) | 0.0022*** (0.0008) | 0.1078*** (0.0113) | 0.1815** (0.0343) | 0.2609 (0.0120) | 0.4024*** (0.0873) |
| *PCAP*ECI* | 0.0005** (0.0001) | 0.0006 (0.0005) | 0.0005* (0.0002) | 0.0010** 0.0004 | 0.0128*** (0.0017) | 0.0070** (0.0010) | 0.0111** (0.0010) |
| | | | | | | | |
| *Hausman test* | | 39.35 [0.0000] | | Not applicable (N/A) | | | |
| *AR(1)* | Not applicable (N/A) | | | -3.34[0.001] | -1.15[0.250] | -1.55[0.122] | -2.02[0.044] |
| *AR(2)* | | | | 2.13[0.033] | 0.56[0.576] | 0.90[0.368] | 0.22[0.236] |
| *Hansen J-test* | | | | 9.61[0.996] | 9.61[0.996] | 0.88[0.831] | 0.88[0.138] |
| *Countries* | 17 | 17 | 17 | 17 | 17 | 17 | 17 |
| *Observation* | 442 | 442 | 442 | 408 | 408 | 425 | 425 |

Note: Values in parentheses are standard errors and p-values for those in square parentheses, while *** p<0.01, ** p<0.05, * p<0.1 denote 1%, 5%, and 10% levels of significance.

## 5.0 Conclusion and Recommendations

While revisiting the human capital-led growth hypothesis, this study controls for the role of economic complexity, which reflects national production capabilities, with more complex economies predicted to have more educated workers and competitive environments. Employing dynamic panel model estimators such as difference GMM and system GMM, we show results that suggest that the complexity dynamics of economics in SSA are too low to significantly impact the growth process in SSA. In other words, despite the economic complexity regarded as a high degree of knowledge accumulation that enhances the ability of a country to produce a variety of sophisticated products typically characterized by high and increasing returns, it is the traditional measure of human capital, such as the average year of school, which appears to matter most for growth in SSA. However, we find that economic complexity can foster not only the impact of human capital on growth but also the impact of physical capital on growth. The positive association between physical capital and economic growth indicates that capital investment is a strong factor in improving growth in the SSA. Therefore, it is recommended that a framework that promotes the judicious combination of both human capital and physical capital as two forms of productivity enhancement to accelerate the economic growth process in the SSA. The way to go is to remove the bottlenecks in infrastructural development by paying more attention to factors such as economic complexity and institutional quality that are capable of fostering the development of both human and physical capital.

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