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PRODUCTIVITY GROWTH, HUMAN CAPITAL AND DISTANCE TO FRONTIER IN SUB-SAHARAN AFRICA

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We examine the contribution of human capital to productivity growth, innovation and adoption of technology for a sample of SSA countries between 1960 and 2003. We find that human capital does not exert statistically significant effect on productivity growth. However, after decomposing total factor productivity into its main components, our results show that the effect of human capital on efficiency change is positive and statistically significant; whilst its effect on technical change is statistically insignificant. Our results also show that proximity to the frontier is a significant determinant of productivity growth in SSA, but the growth enhancing effects of human capital as countries move closer to the frontier is insignificant.

Keywords: Productivity Growth, Human Capital Sub-Saharan Africa
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1. INTRODUCTION

"Education .... is both the seed and the flower of economic development."
Harbison and Myers (1965, p xi)

There is a renewed emphasis on human capital or the educational attainment of the labour force as a significant factor to accelerate productivity and economic growth. It is widely accepted that nations cannot raise the quality of their citizens without substantial and consistent investment in human capital. Theoretical models of human capital and economic growth are built around the hypothesis that knowledge and skills embodied in humans directly raise productivity and increase an economy's ability to develop and to adopt new technologies. The earlier work by Nelson and Phelps (1966) argued that a more educated labour force would adopt new technologies faster, consequently closing

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the technological gap. This was given complementary theoretical support by the new endogenous growth theories (Romer, 1990a; Aghion and Howitt, 1992) who described the stock of human capital as the engine of growth through innovation. Romer (1990b) argues that the level of human capital may have an influence on the growth of productivity both directly and through the effect on the speed of adoption of the "catching- up" process.

Stemming from these foundations, Benhabib and Spiegel (1994, 2005), Barro and Sala-i-Martin (1997) and Barro (1991) demonstrate that the stock of human capital not only enhances the ability of a country to develop its own technological innovation, but also increases its capacity to adopt the already existed knowledge elsewhere and thereby facilitates growth. On the other hand, Lucas (1988) and Mankiw *et al.* (1992) argue that it is not the stock of human capital but rather the accumulation of human capital which is the main source of growth across countries.

Surprisingly, however, the empirical evidence on the role of human capital in explaining economic growth appears to be mixed.[1] A number of empirical studies find negative or no correlation between economic growth and human capital (Benhabib and Spiegel, 1994; Islam, 1995); while other studies point to a positive and significant effect of human capital on growth (Mankiw *et al*., 1992; Caselli *et al*., 1996; Hoeffler, 2002). In the specific context of sub-Saharan Africa, Ndulu and O'Connell (2003) report that enrolment rates, educational attainment and human capital accumulation add relatively little to the explanation of cross country growth in these countries.

In this paper we analyse the effects of human capital in fostering productivity growth. Indeed, we empirically explore how human capital affects total factor productivity (TFP) growth, technical efficiency and technical change. The focus on productivity is motivated by its importance in explaining overall growth. To be sure, recent empirical literature on economic growth investigating the proximate causes of the enormous differences in per capita income across countries usually indicate that these differences in incomes are largely a consequence of differences in TFP growth (Krugman, 1994; Klenow and Rodriguez-Clare, 1997; Hall and Jones, 1999; Easterly and Levine, 1997). In the context of Sub Saharan Africa, results from aggregative growth accounting studies indicate a more prominent role to the total factor productivity residual in explaining its relatively slow growth over the last four decades (Collins and Bosworth, 2003; and Ndulu and O'Connell, 2000, 2003). Along the same line, Devarajan *et al*. (2003) argue strongly, that TFP has played a major role in explaining this growth performance and, therefore, it is TFP rather than the level of investment that has been the constraint to growth. Progress reports of the Millennium Development Goals (MDGs) and Poverty Reduction Strategy Papers (PRSPs) in most Sub-Saharan African countries indicate that

[1] Some economists (Temple, 1999; Krueger and Lindhal, 2001) have attributed these mixed results to significant measurement error and the endogeneity problem in educational attainment (Bils and Klenow, 2000).

a sustainable progress in productivity growth is required in order to achieve the targets set out in these programs.

At the empirical level, a number of studies have investigated the linkage between human capital and productivity, albeit most of these studies focus on OECD countries. The technological views of human capital have received more empirical support. The work of Benhabib and Spiegel (1994, 2005), Barro and Sala-i-Martin (1995) and Barro (1998), showed that both the initial schooling level and its interaction with a measure of the technology gap with the frontier were positively associated with subsequent growth. Benhabib and Spiegel (1994) using cross-country data from 78 countries over the period of 1965 to 1985 and an alternative endogenous model, where productivity growth is the result of a combination of innovation and adoption of technology, found that the growth rate of productivity depends on a nation’s human capital stock level when they accounted for differences in initial technology levels across countries. Benhabib and Spiegel (1994) concluded that the role of human capital is indeed one of facilitating adoption of technology from abroad and creation of appropriate domestic technologies rather than entering on its own as a factor of production. They also suggested that technological “catch-up” remains a significant element in growth and, that, countries with higher education tend to close the technology gap faster than others.

We note, however, that the vast majority of the existing empirical studies have only looked at the effect of human capital on productivity growth. In other words, the differential effect of human capital on technical change and efficiency change has been overlooked. To be sure, explained in the context of production possibilities frontier, productivity growth can be decomposed into two mutually exclusive and exhaustive components; technical change (innovation) and efficiency change (adoption of technology).

Two recent studies have attempted, indirectly, to address this issue by using the composition of human capital i.e. primary, secondary and tertiary education attainment (Vandenbussche *et al*., 2006; Ang *et al*., 2011). The study by Vandenbussche *et al*. (2006) showed that the growth-enhancing margin in OECD countries is that of skilled human capital (tertiary education) rather than that of unskilled human capital (primary and secondary education). The authors interpreted these findings as meaning that human capital contributes to productivity growth via the channels of innovation in OECD countries. However, Ang *et al*. (2011) showed that human capital (skilled and unskilled) neither contributes to innovation nor to the adoption of technology in the context of low income countries. These findings by Ang *et al.* (2011) are however inconsistent with the preposition by Vandenbussche *et al*. (2006) and counter intuitive, given the predominantly unskilled labour in low income countries (see Barro and Lee, 2010).

Unlike the studies by Vandenbussche *et al*. (2006) and Ang *et al*. (2011) which employed the composition of human to examine the connection between human capital and productivity growth via the channels of innovation and adoption of technology in this paper we attempt to investigate the direct effect of human capital on productivity growth-and on innovation and adoption of technology for a sample of 19 Sub-Sahara

African countries for the period 1960-2003. To this end, we first use the Malmquist productivity index to compute productivity change, technical change and efficiency change for these countries. Then using various panel data techniques (and two alternative human capital datasets) we empirically explore the role played by human capital. We find that the contribution of human capital to overall productivity growth is not robust across the different specifications. We also find that human capital does not contribute to innovation but has significantly positive effects on the adoption of technology in SSA. Moreover, we find that the growth enhancing effects of human capital as SSA countries move towards the world technological frontier is also not significant. Our result with regard to the positive role of human capital on the adoption of technology in SSA differs from that of Ang *et al*. (2011). This may primarily be due to the fact that Ang *et al*. (2011) examine this relationship indirectly, using the composition of human capital, i.e., primary and secondary educational attainment and overall productivity growth. However, the current study looks at this relationship directly, using total educational attainment and efficiency change index (adoption of technology).

The rest of the paper is organised as follows. In Section 2, we discuss the empirical methodology and the data. Section 3 presents the main results and their interpretation. Concluding remarks are left to Section 4.

2. METHODOLOGY AND DATA DISCUSSION

2.1. Malmquist Productivity Index

In measuring TFP, the vast majority of the existing studies have adopted the growth accounting approach (Solow, 1956). However, a major issue with the growth accounting method, also known as the residual approach, is that it assumes that all the units of production are efficient and no distinction is made between technical progress and changes in technical efficiency. In other words, no separate adjustment for technical improvement (change in efficiency) embodied in labour or capital stock is considered. The frontier approach-which follows from the works of Debreu (1951), Koopmans (1951), and Farell (1957)- provides a route to address this deficiency.

The frontier approach, broadly speaking, could be divided into two main groups: parametric-stochastic and non-parametric-deterministic. The parametric-stochastic frontier analysis (SFA) requires the functional specification of the production as well as the distributions of the stochastic parts but are considered robust against measurement errors. The nonparametric-deterministic method data envelopment analysis (DEA), which uses linear programming methods to fit a piecewise linear quasi-convex hull around the data, does not require functional form assumptions or distributional assumptions but are more sensitive to outliers.

Both the parametric SFA and the non-parametric Malmquist productivity index have been employed in the growth literature with respect to the measurement of productivity and its components - technical change and technical efficiency change. However, it is worth noting that results of most empirical studies employing the SFA show that estimates of TFP growth and components vary in sign and magnitudes according to different econometric specifications. In some cases, model specifications under the SFA are counter intuitive producing results which are not consistent with the empirical literature (Kumbhakar and Wang, 2005; Garcia *et al*., 2008). The Malmquist productivity index method appears to be common in the study of productivity of nations than the SFA (see studies by Färe *et al*., 1994; Taskin and Zaim, 1997; Maudos *et al*., 1999; Rao and Coelli, 1999; Kruger, 2003; Headey *et al*., 2010). Lovell (1996, p. 329), for instance, finds the Malmquist productivity index approach based on the data envelopment analysis (DEA), "*to have achieved a more satisfactory reorientation toward productivity measurement than the SFA has*". Nonetheless, in this paper, we use the output based Malmquist productivity index approach in a macroeconomic context, where, the countries are producers of output (real GDP) given inputs (physical capital stock and labour), to compute productivity growth, technical change and efficiency change for countries in our sample. A detailed exposition of the Malmquist productivity index and the technique of DEA necessary to make the Malmquist productivity index calculations operational are presented in Appendix A.

2.2. Econometric Specification

To study the effect of human capital, we adopt a specification that builds on the empirical growth model of Vandenbussche *et al.* (2006):

$$\begin{aligned}\Delta \ln Y_{it} = \gamma_{0i} + \gamma_1 \ln H_{i,t} + \gamma_2 \left(\frac{1}{Dist.Front_{i,t}} \right) + \gamma \ln H_{i,t} \times \left(\frac{1}{Dist.Front_{i,t}} \right) \\ + \xi Z_{it} + \gamma_t + \varepsilon_{it},\end{aligned} \tag{1}$$

where Y represents our dependent variables (TFP change, technical change and efficiency change); H is human capital; *Dist.Front* stands for distance to frontier, and thus, $1/Dist.\ Front$ represents proximity to technological frontier; $\ln H \times (1/Dist.Front)$ captures the interaction effect of the two variables; Z denotes a vector of all other potential control variables that are likely to affect our respective dependent variables; γ_{0i} reflects country dummies which control for unobserved permanent differences in TFP change, technical change and efficiency change that may exist in these countries, γ_t captures the unobservable individual invariant time effects and, ε_{it} is the error term; i and t represent individual countries and time respectively.

The panel data set contains repeated observations over time for 19 SSA countries. Equation (1) is estimated in 5-year intervals to filter out the influence of business cycles

(Ang *et al.*, 2011). We employ three different panel data approaches to ensure robustness of the results across various econometric techniques. First Equation (1) is estimated using the pooled-OLS technique. Then because of potential endogeneity of some of the right hand-side variables and potential presence of measurement error, we adopt two instrumental variable approaches, namely the enhanced instrumental variable (IV) (Baum *et al*., 2007) and the System -Generalised Method of Moments (SYS-GMM) (Arellano and Bover, 1995; Blundell and Bond, 1998).

Based on the theoretical and empirical discussions, we expect the sign of the estimated coefficient of human capital to be positive across TFP change and components. Increases in the distance to the frontier are expected to be negatively associated with productivity. This follows the prediction of the hypothesis of the advantage of backwardness by Gerschenkron (1952).[2] The interaction term $\ln H \times (1/Dist.Front)$, which captures the growth enhancing effects of human capital when countries are closer to the frontier would be based on the level of educational attainment. Given that, human capital would be more important in this case for countries with higher levels of skilled labour, we expect the interaction effect for our sample of SSA countries that have higher levels of unskilled human capital to be unimportant or negative, because this labour group imitates the innovations in the frontier country.

2.3. Data Discussion

We start by discussing the dataset related to the derivation of the Malmquist productivity index. The dataset is a panel of 83 countries, including our sample of 19 SSA countries over the 1960-2003 period.[3] The dataset is expanded to include some OECD and other countries to enable us determine the globally efficient frontier. The data used for the computation of the TFP change, technical change, and efficiency change are the logs of real GDP, physical capital stock and labour force. The real GDP data is derived from the Heston, Summers and Aten (2006) database (Penn World Table 6.2). In line with the existing literature (see Collins and Bosworth, 2003; Ndulu and O'Connell, 2003), the total labour force is measured by the economic active population that is the population aged between 15 and 64 years and sourced from the WDI (2008). We follow the methodology by Nehru and Dhareshwar (1993) for our dataset on physical capital stock. Using the perpetual inventory method with a revised depreciation rate of 0.05 percent we extend the dataset to 2002.[4] Distance to frontier is calculated

[2] Countries which are further behind the technology frontier should experience higher TFP growth due to lower effective costs of imitation and innovation, thereby allowing a more rapid catch-up to the technology frontier.

[3] See Appendix B, Table B2 for list of countries.

[4] We obtain the dataset on physical capital stock and Collins and Bosworth measure of human capital index from Susan Collins. We are grateful to Susan Collins for access to the data.

from the DEA scores. Countries on the technology frontier have a value of 1. Proximity to frontier is the inverse of the distance to frontier.

For the total human capital variable, two different data sets on educational attainment are used in order to check for sensitivity and robustness of our educational attainment measure.[5] Firstly, we use the educational attainment dataset constructed by Collins and Bosworth (2003), henceforth 'CB'. CB used an annual average of the series on years of schooling from Barro and Lee (2000) and Cohen and Soto (2001)[6] to construct a human capital index. CB's measurement is a weighted average of the percentage of a country's population, 15 and over having attained 7 levels of schooling, 1 for no schooling, to 7 for completed beyond secondary school. Secondly, we use Barro and Lee (2010), henceforth 'BL', dataset on total human capital and human capital compositions. This new dataset exploits new sources of information and introduce different corrections to improve the signal-to-noise ratio in the schooling series. The educational attainment estimates of BL are measured by the mean years of schooling in the population aged 15 years and over. We note from the expanded dataset of BL that the mean years of schooling in the tertiary group in our SSA sample is much lower than that of the mean primary educational attainments. With reference to other developing regions, SSA is lagging behind other developing regions in the areas of higher education, with abysmally low tertiary enrolment rate and low access to information and knowledge.

One modification we introduce to the original Vandenbussche *et al.* (2006) model specification is the inclusion of a set of control variables-captured by Z_{it} in Equation (1). This is to ensure that our results are not driven by the choice of model specifications. The set of control variables we use include population, government consumption (as a percentage of GDP) and inflation which are taken from the WDI (2008); openness (measured as the ratio of exports plus imports to GDP), derived from the Penn World Table 6.2; and the quality of institutions and democracy obtained from The Polity IV Project (Marshall and Jaggers, 2009).[7] The descriptive statistics of these variables are shown in Appendix B, Table B1.

[5] The robustness and sensitivity checks are indispensable because measurement error is an issue in the literature due to the poor quality of human capital measurements.

[6] Cohen and Soto (2001) developed a global data set, covering 95 countries. They compute educational attainment at the beginning of each decade for the period of 1960 to 2000. For some countries, they had more recent census information than that used by Barro and Lee (2000). More importantly, they use age-specific data in the available censuses to construct estimates of educational attainment for each age-cohort in other years for which direct observations were missing. Thus, they only use enrolment data to fill missing age cohort cells.

[7] The POLITY score is computed by subtracting the AUTOC score from the DEMOC score; the resulting unified polity scale ranges from +10 (strongly democratic) to -10 (strongly autocratic).

3. ESTIMATION RESULTS

Before we start discussing our main results, it is worth commenting on the estimates of the Malmquist productivity index exercise. Table B3 in Appendix shows the means of productivity change and its components for the countries of interest. The overall mean estimates over the period shows a decline of 2.4% and 3.3% for TFP growth and the technical change component. The efficiency change component, however, indicates a moderate increase of 0.9%. Countries like Mauritius, Kenya and Senegal have a fair increase in TFP growth. All countries in the SSA sample experienced technical regress or decline in innovation, but the estimates for most countries showed an improvement in efficiency change or adoption of technology.

To ensure robustness of our frontier estimates we perform an *ex ante* outlier detection tests. Indeed, a drawback in the use of the nonparametric approach, adopted in this study, is that it is sensitive to outliers and extreme values in the data. It is therefore important to assess whether the presence of outliers in the data influence the estimates of other countries. For this purpose, we implement two outlier detection tests. First we adopt the Banker and Chang (2006) approach, which postulates that efficiency score greater than 1.2 indicate the presence of outliers. However, in this present context the maximum efficiency score was 1.18; thus indicating the absence of outliers. We also perform the outlier detection technique advanced in Simar (2003), further discussed in Daraio and Simar (2007), and find no evidence of extreme observations driving our frontier estimates within the DEA framework.

Having established the robustness of our estimates, we now turn our attention to the results obtained from estimating Equation (1). To make the discussion easier to follow we start by presenting the results (for each of our dependent variables) with CB as our proxy for human capital. The results related to TFP growth, technical change and efficiency change are portrayed, respectively, by Tables 1, 2 and 3. Then in another set of results we use the BL measure for human capital. The results of the BL estimates are available from the authors upon request.

3.1. TFP Growth, Total Human Capital and Proximity to Frontier

The results in Column (1) of Table 1, which portray the baseline model using the Pooled-OLS, show that, although the impact of human capital (CB) on TFP growth is positive its effect is statistically insignificant. The results also show that the estimated coefficient for the proximity to the frontier is negative and highly significant in statistical term. In Column (2) we augment the baseline model with the interaction term between our human capital proxy and the distance to the frontier variable. The effect of human capital on TFP growth is still insignificant whilst the distance to the frontier variable continue to exert a negative and significant effect on our dependent variable. However, the interaction term is statistically insignificant; albeit positive. In Column (3), further control variables (population, openness, government consumption, inflation, polity) are added. Now the coefficient of human capital turns out to be significant at the 5% level. The findings, related to the proximity variable and the interaction term, remain unchanged.

Due to potential endogeneity of some of the right hand side variables[8] we replicate the above econometric exercise using the IV (Columns 4, 5, and 6) and the GMM-SYS (Columns 7, 8, and 9).[9] The results are remarkably consistent with the Pooled-OLS results, overall. Indeed, the estimated coefficient of human capital remains insignificant, the effect of the distance to the frontier is consistently negative and significant, and the estimated coefficient of the interaction terms is positive but insignificant.

3.2. Human Capital and the Composition of TFP

As aforementioned, one advantage of the non-parametric Malmquist productivity index approach, over the growth accounting, is that it allows the decomposition of TFP into two mutual exclusive components, namely technical change and efficiency change. Our focus here is to find out how human capital affects these two components. Table 2 and C3 present the results related to technical change and efficiency change, respectively.

Starting with technical change, the results in Table 2 show that the effect of human capital is positive but not consistently significant in all the specifications. The distance to the frontier variable is negative but insignificant. The interaction term between human capital and the distance to the frontier exerts no significant effect on technical change. These results suggest that the contribution of human capital to technical change (innovation) in SSA is not significant. The results related to the distance to the frontier indicates the lack of innovation in SSA even when countries are closer to the frontier; whilst the effect of the interaction between human capital and proximity to frontier imply that human capital have no growth enhancing effects as SSA countries move closer to the technology frontier. In other words, the contribution of human capital to innovation as SSA countries move closer to the frontier is insignificant.

[8] We assume that all right hand side variables are endogenous. Internal instruments (i.e., lagged values of the right hand side variables) are used following standard practice in empirical work using these methodologies.

[9] For all our SYS -GMM results we used the small sample bias correction following Windmeijer (2005).

Table 1. TFP Change Estimates Using CB

	Pooled OLS			IV			SYS-GMM		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Human capital (CB)	0.0170	0.0964	0.284**	0.0163	0.0473	0.102	0.0210	0.349	0.277*
	(0.0906)	(0.0958)	(0.103)	(0.110)	(0.111)	(0.103)	(0.0898)	(0.278)	(0.166)
Distance to frontier	-0.0244***	-0.269**	-0.216**	-0.0246**	-0.299**	-0.170**	-0.0823**	-0.966**	-0.480**
	(0.00922)	(0.123)	(0.091)	(0.0117)	(0.140)	(0.0810)	(0.0363)	(0.469)	(0.207)
Human capital * Distance to frontier		0.0728	0.0638		0.0840	0.0460		0.288	0.135
		(0.0457)	(0.0375)		(0.0518)	(0.0297)		(0.180)	(0.0955)
Population (Growth rate)			-0.1948*			-0.1901*			-0.1225
			(0.1108)			(0.1005)			(0.1121)
Openness			0.00213			0.0144			0.0341*
			(0.0111)			(0.0131)			(0.0195)
Govt consumption (% of GDP)			-0.00115***			-0.00104***			-0.000684**
			(0.000295)			(0.000242)			(0.00027)
Inflation			-0.0305			-0.0170			-0.0943
			(0.0265)			(0.0217)			(0.0828)
Polity			0.00118***			0.00115***			0.00212***
			(0.00041)			(0.000423)			(0.00013)
Constant	0.940***	1.066***	0.851***	-0.0590	1.137***	0.981***	0.991***	1.307***	1.204***
	(0.0941)	(0.0930)	(0.0892)	(0.113)	(0.0961)	(0.0868)	(0.101)	(0.236)	(0.219)
Observations	171	171	171	171	171	171	171	171	171
R-squared	0.125	0.173	0.448	0.103	0.166	0.473			
AR(1)							0.017	0.034	0.034
AR(2)							0.125	0.115	0.137
Sargan/ Hansen p –value				0.7989	0.6191	0.6982	0.168	0.493	0.393

Notes: Robust standard errors in parenthesis; Time dummies included in all regressions; *,**,*** represent, respectively, statistical significance at 10, 5 and 1 percent levels.

Table 2. Technical Change Estimates Using CB

	Pooled OLS			IV			SYS-GMM		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Human capital (CB)	0.204***	0.0222	0.201	0.0804	0.504	0.398	0.174*	0.470	0.293*
	(0.0634)	(0.239)	(0.276)	(0.0668)	(0.328)	(0.391)	(0.103)	(0.730)	(0.151)
Distance to frontier	-0.00126	-0.0733	-0.202	-0.00725	-0.395	-0.422	-0.0588	-0.187	-0.106
	(0.0164)	(0.192)	(0.211)	(0.0118)	(0.277)	(0.313)	(0.0372)	(0.677)	(0.182)
Human capital * Distance to frontier		0.0651	0.191		0.365	0.397		0.168	0.0288
		(0.185)	(0.204)		(0.262)	(0.296)		(0.632)	(0.0541)
Population (Growth rate)			0.2315**			0.2169			0.1836
			(0.1118)			(0.2090)			(0.1755)
Openness			0.0213***			0.000536***			0.0201***
			(0.00671)			(0.000161)			(0.00632)
Govt consumption (% of GDP)			-0.000404***			-0.000486***			-0.000532***
			(0.000133)			(0.000141)			(0.000131)
Inflation			-0.0145			-0.00942			-0.00394*
			(0.0228)			(0.0291)			(0.00229)
Polity			-0.000314			-0.00122			0.0143
			(0.000654)			(0.000822)			(0.0511)
Constant	-0.234***	0.989***	0.642**	-0.102	-0.549	-0.424	-0.271***	-0.518	0.693***
	(0.0697)	(0.248)	(0.280)	(0.0688)	(0.346)	(0.421)	(0.0946)	(0.779)	(0.180)
Observations	171	171	171	171	171	171	171	171	171
R-squared	0.330	0.413	0.522	0.346	0.350	0.518			
AR(1)							0.002	0.009	0.081
AR(2)							0.391	0.770	0.551
Sargan/ Hansen p –value				0.2272	0.2373	0.4748	0.231	0.113	0.257

Notes: Robust standard errors in parenthesis; Time dummies included in all regressions; *,**,*** represent, respectively, statistical significance at 10, 5 and 1 percent levels.

With regard to efficiency change, the specifications in Table 3 warrant some comments. Given that technical efficiency change is derived directly from the technical efficiency scores (which is practically the distance to frontier), it makes sense to exclude proximity to frontier $(1/Dist.Front)$ from the technical efficiency change regressions. For this reason, unlike with the TFP and technical change results, we only run two specifications. The reported results show, overall, that human capital exerts a positive and statistically significant effect on efficiency change. This finding is consistent with Vandenbussche *et al.* (2006) hypothesis. Vandenbussche *et al.* (2006) proposes that the adoption of technology involves mostly physical capital and less (educated) human capital, whilst innovation involves highly skilled labour because it is a skill-intensive activity. Our findings indicate that the large masses of the population in SSA who are generally unskilled or less educated (Barro and Lee, 2010) contribute to productivity growth via the adoption of technology as suggested by Vandenbussche *et al.* (2006).

Table 3. Efficiency Change Estimates Using CB

	Pooled OLS		IV		SYS-GMM	
	(1)	(2)	(3)	(4)	(5)	(6)
Human capital (CB)	0.188*	0.342***	0.194*	0.401***	0.346**	0.662**
	(0.101)	(0.111)	(0.105)	(0.120)	(0.159)	(0.318)
Population (Growth rate)		0.00611		-0.00608		-0.00583
		(0.0222)		(0.02733)		(0.0307)
Openness		-0.0201**		-0.000527***		-0.000840*
		(0.00812)		(0.000162)		(0.000465)
Govt consumption		-0.000717***		-0.000725***		-0.00112***
(% of GDP)		(0.000162)		(0.000161)		(0.000368)
Inflation		0.0117		0.00124		0.0780
		(0.0289)		(0.0291)		(0.0932)
Polity		0.000413		0.000634		0.00355
		(0.000781)		(0.00103)		(0.00291)
Constant	0.817***	0.750***	0.810***	-0.357***	0.650***	-0.647**
	(0.107)	(0.118)	(0.111)	(0.119)	(0.168)	(0.296)
Observations	171	171	171	171	171	171
R-squared	0.1938	0.2226	0.058	0.235		
AR(1)					0.041	0.006
AR(2)					0.123	0.519
Sargan/ Hansen p –value			0.6252	0.6320	0.304	0.571

Notes: Robust standard errors in parenthesis; Time dummies included in all regressions; *,**,*** represent, respectively, statistical significance at 10, 5 and 1 percent levels.

3.3. Further Robustness

In addition to adopting various econometric techniques as well as various model specifications we also use an alternative measure of human capital to ensure that the above results are not driven by the choice of human capital proxy. We replicate the above exercises using the BL proxy for human capital. The results are remarkably similar to those using CB as a proxy for human capital. In other words, our main findings remain robust irrespective of the human capital measure we use.

4. CONCLUSIONS

This paper investigated the importance of human capital in explaining total factor productivity growth in Sub-Sahara Africa. Using data for 19 countries, covering the 1960-2003 period and various panel data techniques the study finds that, although the effect of human capital on TFP growth is positive, its effect is statistically insignificant. However, after decomposing TFP growth into its main components, the results show that whilst human capital appears to exert a positive and statistically significant impact on efficiency change (adoption of technology) its effect on technical change (innovation) is found to be insignificant. The finding on efficiency change- which indicates that the stock of human capital in SSA (which is largely unskilled) has a positive and significant effect on the adoption of technology-is consistent with the Vandenbussche *et al.* (2006) argument that the adoption of technology or imitation involves mostly physical capital and less educated or unskilled human capital, whilst innovation is a skill-intensive activity.

Moreover, the results indicate that proximity to the frontier is negatively associated with TFP growth. However, the results also suggest that proximity to the frontier does not enhance the role of human capital in explaining TFP growth nor does it explain innovation.

These findings present some inimitable empirical evidence on the importance of total human capital for policy managers in the SSA region. Although, the level of human capital in SSA is important for the adoption of technology, its insignificant contribution to innovation and overall productivity growth is a major cause of concern. The findings of the study suggest that the lower levels of skilled labour component may have detrimental implications for economic development in SSA. To some extent, the lower levels of skilled labour may partly explain the failure of technological and economic convergence in SSA.

APPENDIX A

A1. Overview of Data Envelopment Analysis (DEA) and Malmquist Productivity Index

In this paper, we measure total factor productivity (TFP) using the Malmquist index methods described in Färe *et al*. (1994) and Coelli and Rao (1999) to measure productivity growth in different countries. This approach uses data envelopment analysis (DEA) methods to construct a piece-wise linear production frontier for each year in the sample. A brief description of basic concepts, the technique of DEA and its use in the computation of the Malmquist TFP index are discussed below.

Production Technology

Malmquist index is based on the existence of a production technology which transforms multi-dimensional input vectors, say *x*, into multi-output vectors, *y*. The production technology is assumed to satisfy a number of basic properties or axioms. These are: (i) possibility of inactivity; (ii) weak or strong disposability of outputs; (iii) weak or strong disposability of inputs; (iv) closed and bounded production possibility sets; (v) closed input sets; and (vi) input and output convexity.[10] Of these the most important axioms are the strong and weak versions of output and input disposability. In addition to these, the present study assumes that the production technologies satisfy (global or local) constant returns to scale.[11]

Distance Functions

The Malmquist TFP index is defined using distance functions. One may define input distance functions and output distance functions. For purposes of this paper, we consider only output distance functions.

A production technology, satisfying standard axioms, may be defined using the output (possibility) set, $P(x)$, which represents the set of all output vectors, *y*, which can be produced using the input vector, *x*. That is,

$$P(x) = \{y : x \text{ can producey}\}. \tag{A1}$$

The output distance function is defined on the output set, $P(x)$, as:

[10] See Fare and Primont (1995, p. 27) for details of these axioms.

[11] Global constant returns to scale is applicable to the case where single output, real GDP, is used in productivity analysis. Local returns to scale are more meaningful when the two-dimensional output vector, real GDP and inequality, is considered.

$$d_0(x,y) = \min\{\delta : (y/\delta) \in P(x)\} . \tag{A2}$$

The distance function, $d_0(x,y)$, will take a value which is less than or equal to one if the output vector, y, is an element of the feasible production set, $P(x)$. Furthermore, the distance function will take a value of unity if y is located on the outer boundary of the feasible production set, and will take a value greater than one if y is located outside the feasible production set.[12]

Data Envelopment Analysis (DEA)

DEA is a linear-programming methodology, which uses data on the input and output quantities of a group of countries (or firms or whatever) to construct a piece-wise linear surface over the data points. This frontier surface is constructed by the solution of a sequence of linear programming problems - one for each country in the sample. The degree of technical inefficiency of each country (the distance between the observed data point and the frontier) is produced as a by-product of the frontier construction method.

DEA can be either input-orientated or output-orientated. The two measures provide the same technical efficiency scores when a constant returns to scale (CRS) technology applies, but are unequal when variable returns to scale (VRS) is assumed. In this study, we have selected an output orientation because we believe it would be fair to assume that, in the case of countries, each country attempts to maximise output from a given set of inputs or resource endowments, rather than the converse.

If one has data on N countries in a particular time period, the linear programming (LP) problem that is solved for the i-th country in an output-orientated DEA model is as follows:

$$\begin{aligned} &\max_{\varphi,\lambda} \varphi, \\ &\quad st \quad -\varphi y_i + Y\lambda \geq 0, \\ &\qquad\quad x_i - X\lambda \geq 0, \\ &\qquad\quad \lambda \geq 0, \end{aligned} \tag{A3}$$

where

y_i is a $M \times 1$ vector of output quantities for the i-th country;

x_i is a $K \times 1$ vector of input quantities for the i-th country;

Y is a $N \times M$ matrix of output quantities for all N countries;

X is a $N \times K$ matrix of input quantities for all N countries;

λ is a $N \times 1$ vector of weights; and

[12] This becomes relevant when we consider inter-period distance measures.

φ is a scalar.

φ will take a value greater than or equal to one, and that $\varphi - 1$ is the proportional increase in outputs that could be achieved by the *i*-th country, with input quantities held constant. $1/\varphi$ defines a technical efficiency (TE) score which varies between zero and one (this is the output-orientated TE score reported in our results). Efficient countries on the frontier have scores equal to 1 and inefficient countries have scores less than 1.The above LP is solved *N* times - once for each country in the sample.

Malmquist TFP Index Computation and Decomposition using DEA

The Malmquist TFP index measures the TFP change between two data points (e.g., those of a particular country in two adjacent time periods) by calculating the ratio of the distances of each data point relative to a common technology. Following Färe *et al.* (1994), the Malmquist (output-orientated) TFP change index between period s (the base period) and period t is given by

$$m_o(y_s,x_s,y_t,x_t) = \left[\frac{d_o^s(y_t,x_t)}{d_o^s(y_s,x_s)} \times \frac{d_o^t(y_t,x_t)}{d_o^t(y_s,x_s)}\right]^{1/2}, \tag{A4}$$

where the notation $d_o^s(x_t,y_t)$ represents the distance from the period *t* observation to the period *s* technology. A value of m_o greater than one will indicate positive TFP growth from period *s* to period *t* while a value less than one indicates a TFP decline. Equation (A4) is, in fact, the geometric mean of two TFP indices. The first is evaluated with respect to period s technology and the second with respect to period t technology.

An equivalent way of writing this productivity index is

$$m_o(y_s,x_s,y_t,x_t) = \frac{d_o^t(y_t,x_t)}{d_o^s(y_s,x_s)}\left[\frac{d_o^s(y_t,x_t)}{d_o^t(y_t,x_t)} \times \frac{d_o^s(y_s,x_s)}{d_o^t(y_s,x_s)}\right]^{1/2}, \tag{A5}$$

where the ratio outside the square brackets measures the change in the output-oriented measure of Farrell technical efficiency between periods *s* and *t*. The remaining part of the index in Equation (A5) is a measure of technical change.

The required distance measures for the Malmquist TFP index can be calculated using DEA-like linear programs (Färe *et al.*, 1994).

APPENDIX B

Table B1. Summary Statistics

	Mean	Std. Dev.	Min	Max
Real GDP	1.01E+08	3.46E+08	209575.9	6.14E+09
Capital stock	4749557	5.48E+07	11.8336	1.70E+09
Labour	2.28E+07	8.27E+07	161881	7.70E+08
TFP change index	0.9807102	0.0516888	0.7148	1.12575
Technical change index	0.9722828	0.0494184	0.7646	1.08975
Efficiency change index	1.012885	0.0494888	0.8745	1.1874
Proximity	0.3734341	0.1647433	0.1463209	0.9314365
CB	3.093734	1.926922	0.1909	8.2929
BL	1.052976	0.0488956	0.98198	1.20621
Population	1.57e+07	2.00e+07	719000	1.30e+08
Openness	61.67332	41.55516	17.684	350.89
Inflation	17.28402	25.75491	-1.429057	158.4546
Gov’t cons	248.2928	169.996	1	577.4
Polity	-2.425354	5.726878	-9	10

Notes: Real GDP, Capital stock are in PPP$; TFP index, Technical change and Efficiency change index are indices computed from the Malmquist Index; CB and BL measure educational attainment for Collins and Bosworth, and Barro and Lee respectively. CB is an index for human capital. BL is mean years of schooling. Gov’t Consumption is a % of GDP.

Table B2. List of Countries

Sub- Saharan Africa			
Cameroon	Madagascar	Nigeria	Tanzania
Cote D'Ivoire	Malawi	Rwanda	Uganda
Ethiopia	Mali	Senegal	Zambia
Ghana	Mauritius	Sierra Leone	Zimbabwe
Kenya	Mozambique	South Africa	
Asia			
China	Philippines	Taiwan	Pakistan
Indonesia	Singapore	Thailand	Sri Lanka
Malaysia	South Korea	India	
Latin America			
Argentina	Dominican Rep.	Honduras	Peru
Bolivia	Ecuador	Jamaica	Trinidad and Tobago
Brazil	El Salvador	Mexico	Uruguay
Chile	Guatemala	Nicaragua	Venezuela
Colombia	Guyana	Panama	
Costa Rica	Haiti	Paraguay	

OECD			
Australia	Denmark	Ireland	Portugal
Austria	Spain	Iceland	Sweden
Belgium	Finland	Italy	United States
Canada	France	Japan	
Switzerland	Great Britain	Netherlands	
Germany	Greece	New Zealand	
Others			
Algeria	Iran	Jordan	Tunisia
Egypt	Israel	Morocco	

Table B3. Mean Country Malmquist Productivity Index and Decomposition, 1960-2002

Country	Malmquist TFP Change	Efficiency Change	Technical Change
Mauritius	1.007	1.037	0.971
Kenya	1.003	1.025	0.979
Senegal	1.000	1.02	0.98
Mali	0.998	1.019	0.98
Zimbabwe	0.995	1.015	0.98
Tanzania	0.994	1.014	0.98
Cote d' Ivoire	0.993	1.016	0.978
Cameroon	0.984	1.01	0.975
Ghana	0.984	1.004	0.98
Madagascar	0.982	1.00	0.982
Ethiopia	0.979	1.00	0.979
Sierra Leone	0.976	1.009	0.967
South Africa	0.976	1.019	0.958
Rwanda	0.974	0.999	0.975
Mozambique	0.971	1.01	0.961
Malawi	0.967	0.99	0.977
Nigeria	0.961	0.978	0.982
Uganda	0.905	0.999	0.906
Zambia	0.904	1.015	0.89
Overall Mean	0.976	1.009	0.967

Source: Authors' own calculations; All numbers in the table are index numbers. Subtracting 1 from the number reported in the table gives average increases or decreases per annum for the relevant time period and relevant performance measure.

REFERENCES

Aghion, P.Y.H., and P.P. Howitt (1992), "A Model of Growth through Creative Destruction," *Econometrica*, 60**,** 323-351.

Ang, J.B., J.B. Madsen, and M.R. Islam (2011), "The Effects of Human Capital Composition on Technological Convergence," *Journal of Macroeconomics*.

Arellano, M., and O. Bover (1995), "Another Look at the Instrumental Variable Estimation of Error-Components Models," *Journal of Econometrics*, 68**,** 29-51.

Banker, R.D., and H**.** Chang (2006), "The Super-Efficiency Procedure for Outlier Identification, Not for Ranking Efficient Units," *European Journal of Operational Research*, 175, 1311-1321.

Barro, R.J. (1991), "Economic Growth in a Cross Section of Countries," *The Quarterly Journal of Economics*, 106**,** 407-443.

_____ (1998), *Determinants of Economic Growth: A Cross-Country Empirical Study*, Lionel Robbins Lectures, MIT Press.

Barro, R.J., and J.W. Lee (1994), *Data Set for a Panel of 138 Countries*, Harvard Univ.

_____ (2000), "International Data on Educational Attainment Updates and Implications," NBER Working Paper, 7911, National Bureau of Economic Research, Inc.

_____ (2010), "A New Data Set of Educational Attainment in the World, 1950-2010," NBER Working Paper, 15902, National Bureau of Economic Research, Inc.

Barro, R.J., and X. Sala-i-Martin (1995), *Economic Growth*, McGraw-Hill, New York.

_____ (1997), "Technological Diffusion, Convergence, and Growth," *Journal of Economic Growth*, 2**,** 1-26.

Baum, C.F., M.E. Schaffer, and S. Stillman (2007), "Enhanced Routines for Instrumental Variables/Generalized Method of Moments Estimation and Testing," *Stata Journal*, 7**,** 465-506.

Benhabib, J., and M.M. Spiegel (1994), "The Role of Human Capital in Economic Development Evidence from Aggregate Cross-Country Data," *Journal of Monetary Economics*, 34**,** 143-173.

_____ (2005), "Human Capital and Technology Diffusion," *Handbook of Economic Growth*, 1**,** 935-966.

Bils, M., and P.J. Klenow (2000), "Does Schooling Cause Growth?" *American Economic Review*, 1160-1183.

Blundell, R., and S. Bond (1998), "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models," *Journal of Econometrics*, 87**,** 115-143.

Caselli, F., G. Esquivel, and F. Lefort (1996), "Reopening the Convergence Debate: A New Look at Cross-Country Growth Empirics," *Journal of Economic Growth*, 1**,** 363-389.

Coelli, T.J., and D. Rao (2003), *Total Factor Productivity Growth in Agriculture: A Malmquist Index Aanalysis of 93 Countries, 1980-2000*.

Cohen, D., and M. Soto (2001), "Growth and Human Capital: Good Data, Good Results," OECD Developing Centre Working Papers, 179, OECD Publishing.

Collins, S.M., and B. Bosworth (2003), “The Empirics of Growth: An Update,” *Brookings Papers on Economic Activity*, 2**,** 113-206.

Daraio, C., and L. Simar (2007), *Advanced Robust and Nonparametric Methods in Efficiency Analysis: Methodology and Applications*, Springer, New York.

Debreu, G. (1951), “The coefficient of resource utilization,” *Econometrica: Journal of the Econometric Society***,** 273-292.

Devarajan, S., W.R. Easterly, and H. Pack (2003), “Low Investment Is Not the Constraint on African Development,” *Economic Development and Cultural Change***,** 547-571.

Easterly, W. and R. Levine (1997), “Africa’s Growth Tragedy: Policies and Ethnic Divisions,” *Quarterly journal of Economics*, 112**,** 1203-1250.

Färe, R., S. Grosskopf, M. Norris, and Z. Zhang (1994), “Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries,” *The American Economic Review***,** 66-83.

Farrell, M.J. (1957), “The Measurement of Productive Efficiency,” *Journal of the Royal Statistical Society, Series A (General)*, 120**,** 253-290.

Garcia, F., R. César De Souza, and J.O. Pires (2008), “Technical Change: It Should Be Positive and Make Sense!” *Economics Letters*, 100**,** 388-391.

Gerschenkron, A. (1952), “An Economic History of Russia,” *The Journal of Economic History*, 12**,** 146-159.

Hall, R.E., and C.I. Jones (1999), “Why Do Some Countries Produce So Much More Output Per Worker Than Others?” *Quarterly Journal of Economics*, 114**,** 83-116.

Harbison, F.H., and C.A. Myers (1965), *Manpower and Education: Country Studies in Economic Development*, McGraw-Hill.

Headey, D., M. Alauddin, and D. Rao (2010), “Explaining Agricultural Productivity Growth: An International Perspective,” *Agricultural Economics*, 41**,** 1-14.

Heston, A., R. Summers, and B. Aten (2006), “Penn World Table Version 6.2,” Center for International Comparisons at the University of Pennsylvania (CICUP), 18.

Hoeffler, A.E. (2002), “The Augmented Solow Model and the African Growth Debate,” *Oxford Bulletin of Economics and Statistics*, 64**,** 135-158.

Islam, N. (1995), “Growth Empirics: A Panel Data Approach,” *The Quarterly Journal of Economics*, 110**,** 1127.

Klenow, P., and A. Rodriguez-Clare (1997), “Economic Growth: A Review Essay,” *Journal of Monetary Economics*, 40**,** 597-617.

Koopmans, T.C. (1951), *Activity Analysis of Production and Allocation*, New York.

Krüger, J.J. (2003), “The Global Trends of Total Factor Productivity: Evidence from the Nonparametric Malmquist Index Approach,” *Oxford Economic Papers*, 55**,** 265-286.

Krueger, A., and M. Lindahl (2001), “Education for Growth: Why and for Whom,” *Journal of Economic Literature*, 39**,** 1101-1136.

Krugman, P. (1994), *The Age of Diminishing Expectations: US Economic Policy in the 1990s*, revised and updated edition, Cambridge: MIT Press.

Kumbhakar, S.C., and H.J. Wang (2005), “Estimation of Growth Convergence Using a Stochastic Production Frontier Approach,” *Economics Letters*, 88**,** 300-305.

Lovell, C.A.K. (1996), "Applying Efficiency Measurement Techniques to the Measurement of Productivity Change," *Journal of Productivity Analysis*, 7**,** 329-340.

Lucas, R.E. (1988), "On the Mechanics of Economic Development," *Journal of Monetary Economics*, 22**,** 3-42.

Malmquist, S. (1953), "Index Numbers and Indifference Surfaces," *Trabajos de Estadística y de Investigación Operativa*, 4**,** 209-242.

Mankiw, N.G., D. Romer, and D.N. Weil (1992), "A Contribution to the Empirics of Economic Growth," *The Quarterly Journal of Economics*, 107**,** 407.

Marshall, M., and K. Jaggers (2009), *Polity IV Project: Political Regime Characteristics and Transitions, 1800-2007*.

Maudos, J., J.M. Pastor, and L. Serrano (1999), "Total Factor Productivity Measurement and Human Capital in OECD Countries," *Economics Letters*, 63**,** 39-44.

Ndulu, B., and S.A. O'Connell (2000), "Background Information on Economic Growth," AERC Explaining African Economic Growth Project, African Economic Research Consortium.

_____ (2003), "Revised Collins/Bosworth Growth Accounting Decompositions," *AERC Explaining African Economic Growth Project Paper*, African Economic Research Consortium.

Nehru, V., and A. Dhareshwar (1993), "A New Database on Physical Capital Stock: Sources, Methodology and Results," *Revista de Analisti Económico*, 8**,** 37-59.

Nelson, R.R., and E.S. Phelps (1966), "Investment in Humans, Technological Diffusion, and Economic Growth," *The American Economic Review*, 56**,** 69-75.

Rao, D.S.P., and T. Coelli (1999), "Economic Growth, Productivity Change and Inequalty: Methodology for the Assessment of Economic Performance of Nations," Armidale: University of New England/Department of Econometrics/Centre for Efficiency and Productivity Analysis, August.

Romer, P.M. (1990a), "Endogenous Technical Change," *Journal of Political Economy*, 98**,** 71-102.

_____ (1990b), "Capital, Labor, and Productivity," *Brookings Papers on Economic Activity, Microeconomics*, 337-367.

_____ (1989), "Human Capital and Growth: Theory and Evidence," NBER Working Paper, 3173, National Bureau of Economic Research Cambridge, Inc.

Simar, L. (2003), "Detecting Outliers in Frontier Models: A Simple Approach," *Journal of Productivity Analysis*, 20, 391-424.

Solow, R.M. (1956), "A Contribution to the Theory of Economic Growth," *The Quarterly Journal of Economics*, 70**,** 65-94.

Taskin, F., and O. Zaim (1997), "Catching-up and Innovation in High -and Low- Income Countries," *Economics Letters*, 54**,** 93-100.

Temple, J. (1999), "The New Growth Evidence," *Journal of Economic Literature*, 37**,** 112-156.

Vandenbussche, J., P. Aghion, and C. Meghir (2006), "Growth, Distance to Frontier and Composition of Human Capital," *Journal of Economic Growth*, 11**,** 97-127.

Windmeijer, F. (2005), "Finite Sample Correction for the Variance of Linear Two-Step GMM Estimators," *Journal of Econometrics*, 126, 25-51.
World Bank (2008), *World Development Indicators, CD-ROM.*

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