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Assessing the relationships between human capital, innovation and technology adoption: Evidence from sub-Saharan Africa

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A R T I C L E I N F O

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A B S T R A C T

In spite of growing body of research on human capital and innovation, our understanding of the effects and roles of human capital in enhancing innovation and technology adoption in the developing world particularly sub-Saharan Africa remains limited. Using a sample of 45 sub-Saharan African countries from 1960 and 2010, we measure innovation and technology adoption using the Malmquist productivity index approach, and examine the effects of human capital on innovation and technology adoption using different panel data techniques. The study uncovers that the overall mean estimates over the period shows a decline of 0.08% for innovation and a moderate increase of 1.7% for the adoption of technology. Indeed, many countries in the sample experienced technical regress or decline in innovation, but the estimates for most countries showed an improvement in adoption of technology. Human capital appears to exert a positive and statistically significant impact on adoption of technology whilst, its effect on innovation is found to be insignificant.

1. Introduction

For decades, scholars across the social sciences have uncovered human capital as the engine of productivity and growth of nations through innovation and adoption of technology (Nelson and Phelps, 1966; Romer, 1990a; Aghion and Howitt, 1992). It has been suggested that the stock of human capital enhances a country's ability to develop local technological innovation and dissemination of knowledge (World Development Report, 1998). Many contemporary technology and management authors have stressed the importance of new technology adoption in fostering innovation (see Lanzolla and Suarez, 2012; Galang, 2012) as well as facilitating the technology catch-up in the 21st century (Lee, 2013; Zhang and Zhou, 2016). The existing body of research on the relationship between human capital and innovation has concentrated mainly on developed economies where there is a more stable and well-developed institutional environment. Accordingly, it remains unclear whether these findings will hold in an institutional environment of developing economies, where the “rules of the game” are often uncertain (North, 1990; Radjou et al., 2012; George et al., 2012).

Despite these important streams of research, our understanding of how human capital enhances innovations and technology adoption in developing countries remains limited. The primary objective of this study is to examine the effects of human capital in enhancing innovation and technology adoption in developing countries. We focus specifically on sub-Saharan Africa as an empirical setting. Indeed, sub -Saharan Africa represents a promising avenue to shed light on effects of human capital on innovation and adoption of technology (Amankwah-Amoah, 2016b). We use the Malmquist productivity index approach to compute innovation (technical change) and adoption of technology (efficiency change) for 45 sub-Saharan Africa countries. Then using various panel data techniques we empirically explore the role played by human capital on innovation and adoption of technology.

This study offers several contributions to human capital and innovation literature. First, we deviate from much of the existing literature on the relationship between human capital and innovation that has focused on mainly single country (see Dakhli and De Clercq, 2004) by employing data for 45 SSA countries to deepen our understanding of the subject. Thus, we add to the new growing body of scholarly works exploring how governments' STI policy can be formulated to generate economic development and aid poverty reduction efforts in the developing world (Amankwah-Amoah, 2016a; Clark and Frost, 2016; Kaplinsky et al., 2009). In addition, our study contributes to the literature on technology adoption (Lanzolla and Suarez, 2012), human capital theory (Becker, 1964; Schultz, 1961) and innovation (Etzkowitz and Leydesdorff, 2000) by deepening our understanding of the role of human capital in enhancing innovation and facilitating

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technology adoption in SSA. Moreover, the study adds further evidence to the growing streams of research that have shown that the quality of human capital, ability to develop, leverage and utilise might be the most important factors in explaining the effects of human capital on technological achievement rather than the mere possession of human capital by a nation or firm (see Sirmon et al., 2007, 2011).

The remainder of the paper is organized as follows. In the next section, we present a review of the literature on the relationship between human capital, innovation and adoption of technology. We turn our attention to the method adopted and data sources. This is then followed by the results and their interpretations. The final section sets out theoretical and practical implications.

2. Background literature

The general human capital theory (Becker, 1964) provides a theoretical underpinning towards a better understanding of the role of individuals in enhancing innovation and adoption of technology. Human capital theory is about the role of human capital in the production process and the incentives to invest in skills, including pre–labour market investments (in the form of schooling) and on-the-job investments (in the form of training). Human capital refers to an individual's knowledge, skills and experiences, which can be utilised to foster innovation activity (Becker, 1964; Schultz, 1961). For the purposes of this study, however, the key aspect of human capital has to do with the knowledge and skills embodied in people and accumulated through schooling, i.e., educational attainment that is useful in the production of goods, services and further knowledge.

Human capital has an important effect on productivity growth because of its role as a determinant of an economy's capacity to carry out technological innovation (Romer, 1990a) and, for developing countries in particular, to adopt (and adapt and implement) foreign technology. The new wave of the endogenous growth literature (which is connected to the work by Nelson and Phelps, 1966) highlights the role of human capital in promoting productivity growth indirectly through the facilitation of domestic innovation, and diffusion and adoption of new technologies (see Romer, 1990b; Grossman and Helpman, 1990, 1991; Aghion and Howitt, 1992; Aghion et al., 1998). In the form of level of education, one may want to distinguish between basic education and higher education. The former is important for learning-capacity and utilising information, while the latter is necessary for technological innovation. The more education the easier it is to master new technologies (Easterlin, 1981).

As yet there are a very few empirical literature testing the importance of human capital for innovation and adoption of technology. These studies are mostly focused on the developed OECD countries (see Benhabib and Spiegel, 2005; Barro and Sala-I-Martin, 1997; Barro, 1991; Vandenbussche et al., 2006) with only a few studies on developing countries (Ang et al., 2011; Danquah and Ouattara, 2014). The empirical evidence largely demonstrates 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 increase productivity and economic growth. For instance, Benhabib and Spiegel (2005) using a panel dataset covering 19 OECD countries between 1960 and 2000 found that the growth-enhancing margin in OECD countries is that of skilled human capital (tertiary educational attainment) rather than that of total human capital. Benhabib and Spiegel (2005) also estimated the threshold level of human capital needed to exert positive effect on innovation and suggest that countries with sufficiently small human capital stock or low levels of educational attainment may experience slower innovation as compared to the technologically leading nations. Focusing attention on the composition of human capital, Vandenbussche et al. (2006) surmise that the tasks of technology adoption and innovation require different types of human capital. In particular, they assume that unskilled human capital is better suited to technology adoption than to innovation. Their findings on OECD countries show that the growth enhancing properties of human capital to productivity growth depends on its composition. Also, the growth-enhancing margin of innovation in OECD countries is that of skilled human capital (tertiary educational attainment) rather than that of total human capital. The higher growth enhancing effect may be due to the assumption that innovation is a relatively more skill-intensive activity than adoption of technology.

Using a sample of developed and developing countries, Ang et al. (2011) show that, the growth enhancing effects of tertiary education attainment or skilled human capital promotes innovation only in high income countries, thereby supporting the findings of the studies in OECD countries. On the other hand, Ang et al. (2011) also found that tertiary education attainment does not contribute to innovation and growth, and have no growth enhancing effect in low income countries. Using data from SSA countries, Danquah and Ouattara (2014) similarly found that human capital does not exert statistically significant effect on productivity growth. Danquah and Ouattara (2014) attribute the inconsequential contribution of human capital to the negligible growth enhancing effects of human capital as SSA countries move closer to the world technology frontier.

Past studies have also indicated that human capital relates to firms' ability to develop and maintain their competitiveness (Youndt et al., 2004; Ployhart and Moliterno, 2011; Ployhart et al., 2011). Firms' ability to develop business ideas and innovation has been found to be predicated on the quality of human capital held by the employees (Deakins and Whittam, 2000). Similarly, governments' ability to initiate policy and ensure effective implementation is also grounded on quality of human capital within its agencies and enterprises (Amankwah-Amoah, 2016a; Amankwah-Amoah and Sarpong, 2016). It is argued that quality of human capital within the wider society would foster innovation and new technology adoption.

Government-sponsored training courses have been found to be particularly effective in encouraging individuals to upgrade their skills (World Development Report, 2008). By investing scarce national resources in training and information campaigns, government can create conditions for knowledge about new technology for diffusion (World Development Report, 2008).

A number of studies have indicated that it is not the mere possession of human capital that delivers these benefits rather the ability to deploy and utilise them that create conditions for innovation and new business development (see Carmeli, 2004; Amankwah-Amoah, 2015). Notwithstanding these insights, the effects of human capital in enhancing innovation and technology adoption warrants further scholarly attention. Based on the theoretical and empirical discussions on the role of human capita above, we expect the sign of the estimated coefficient of human capital to be positive across innovation and adoption of technology in sub-Saharan Africa.

2.1. Total factor productivity

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 Total Factor Productivity (TFP) growth (see Klenow and Rodriguez-Clare, 1997; Hall and Jones, 1999; Easterly and Levine, 2001; Jerzmanowski, 2007; Danquah and Ouattara, 2015). Explained in the context of production possibilities frontier, TFP growth can be decomposed into two mutually exclusive and exhaustive components; innovation (technical change) and adoption of technology (efficiency change) (see Färe et al., 1994; Lovell, 1996; Kumbhakar and Wang, 2005). Some of the important studies in this specific research context of Sub Saharan Africa indicate a more prominent role to total factor productivity (i.e., innovation and adoption of technology) in explaining its relatively slow growth over the last four decades (see Collins and Bosworth, 2003). Devarajan et al. (2003) argue strongly that the constraint to growth in SSA is due to the deficiency in innovation and technology adoption.

3. Methodology and data discussion

3.1. Malmquist productivity index

The non-parametric Malmquist productivity index has been employed in the growth literature with respect to the measurement of productivity and its components - technical change and technical efficiency change. The Malmquist productivity index method appears to be common in the study of productivity of nations (see studies by Färe et al., 1994; Taskin and Zaim, 1997; Maudos et al., 1999; Rao and Coelli, 1999; Krüger, 2003; Headey et al., 2010). 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 (innovation) and efficiency change (adoption of technology) 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.1.

3.2. Econometric specification

To investigate the role of human capital in explaining innovation and adoption of technology in SSA, we adopt the specification by Ang et al. (2011) below:

$$\Delta \ln Y_{it} = \gamma_{01} + \gamma_1 \ln H_{it} + \xi Z_{it} + \gamma_t + \varepsilon_{it} \quad (1)$$

where Y represents our dependent variables - innovation (technical change) and adoption of technology (efficiency change); H is human capital; 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 innovation and adoption of technology 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.

As indicated, we introduce the inclusion of a set of control variables-captured by Z_{it} in Eq. (1). This is to ensure that our results are not driven by the choice of model specifications. The control variables used in our estimation are population, openness, government consumption (as a percentage of GDP), inflation and the quality of institutions. These control variables have been used extensively in the literature because of its relationship with innovation, adoption of technology and productivity growth. For instance, the population of a country determines the level of participation of the labour force in economic activities. Albeit innovation, adoption of technology and productivity growth may depend on the quality of the labour force, a few studies have attempted to examine the impact of increased population on productivity growth in advanced economies. These studies provide mixed empirical evidence about the role of population and labour participation in facilitating innovation, adoption of technology and productivity growth (see McGuckin and van Ark, 2005; De Jong and Tsiachristas, 2008). Also, empirical evidence is found to suggest that increased trade policy openness will promote innovation and adoption of technology. Grossman and Helpman (1991) and Barro and Sala-i-Martin (1995) among others, have argued that countries that are more open have a greater ability to benefit from technology diffusion and its boosting effect on innovation and productivity growth. Dollar and Kraay (2004) also find evidence that greater openness to trade can generate economies of scale and productivity gains. With respect to government consumption, many studies have shown that government consumption has a positive effect on productivity growth because it generates beneficial externalities stemming from several factors, including multiple interventions to correct market failures (Ghali, 1998). It is also found that some government consumption, particularly on public goods, is necessary to promote productivity growth. However, most empirical studies present strong evidence that large and growing government consumption is not conducive to higher productivity growth or better economic performance. A number of authors have also argued that greater macroeconomic instability—in particular, a high inflation rate—tends to affect the productivity and hence economic performance of a country negatively (see Rajan and Zingales, 1998; Fisman and Love, 2004). Hence, in our empirical specification we use inflation as a macroeconomic stability indicator. Finally, recent empirical studies highlight the importance of good institutions to promote productivity and long-term growth (Acemoglu et al., 2005). Efficient institutions enhance the business environment and, hence, boost investment and productivity. Doucouliagos and Ulubasoglu (2004) for instance, found that higher levels of democracy have a positive and statistically significant effect on productivity growth.

The panel data set contains repeated observations over time for 45 SSA countries. Eq. (1) is estimated in 5-year intervals to filter out the influence of business cycles (see Ang et al., 2011). We employ three different panel data approaches to ensure robustness of the results across various econometric techniques. First Eq. (1) is estimated using the pooled-OLS (POLS) 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 (EIV) (see Baum et al., 2007) and the General Method of Moments System (SYS-GMM) [1] (see Arellano and Bover, 1995; Blundell and Bond, 1998).

3.3. Data measurement and discussion

We start by discussing the dataset related to the derivation of innovation and adoption of technology. The dataset used in this study is a panel of 83 countries (including the 45 SSA countries) for the period 1960–2010. The dataset is expanded to include other countries in order to enable us determine the globally efficient frontier and compute innovation and adoption of technology (see Appendix B, Table B1 for list of countries). The data used for the computation of innovation, and adoption of technology are the logs of real Gross Domestic Product (GDP), physical capital stock and labour force. The real GDP data is derived from the World Development Indicators, WDI (2012). 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 (2012). We follow the methodology by Nehru and Dhareshwar (1993) for our dataset on physical capital stock. Physical capital stock is measured by using the perpetual inventory method with a revised depreciation rate of 0.05 percent. The original dataset was obtained from Collins and Bosworth (2003). We extend the dataset from the year 2000 to 2010.

For the total human capital variable, we use Barro and Lee (2010), henceforth 'BL', dataset on mean educational attainment. 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 (see Table B2, Appendix B). This is a result of clear bias in investments in education towards largely primary education at the expense of higher levels of education, in particular, tertiary education. Governments of SSA countries, likewise, donors and

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

the international development agencies have prioritised funding to primary education (see Ajakaiye and Kimenyi, 2011). Since the adoption of the Millennium Development Goals (MDG) in 2000, a primary focus of international development effort has been directed to meeting the primary school enrolment target specified in the MDG. With reference to the developed and emerging regions, SSA is lagging distantly behind in the areas of higher education, with abysmally low tertiary enrolment rate and low access to information and knowledge. The low levels of tertiary education attainment relate to the large pool of unskilled labour on the continent.

With respect to the set of control variables, population is measured as the total number of people in the country and it is sourced from WDI (2012); government consumption (as a percentage of GDP) is measured as all government current expenditures for purchases of goods and services (including compensation of employees). It is obtained from WDI (2012); inflation as measured by the consumer price index is also taken from the WDI (2012); openness is measured as the ratio of exports plus imports to GDP, and is derived from the Penn World Table 8.1; the quality of institutions and democracy are measured by the POLITY score. The POLITY score is computed by subtracting the AUTOC (autocracy) score from the DEMOC (democracy) score. The resulting unified polity scale ranges from + 10 (strongly democratic) to − 10 (strongly autocratic). This dataset is obtained from Marshall and Jaggers, (2009, Polity IV Project). The descriptive statistics and correlation of these variables are shown in Table 1.

4. Estimation results

Before we start discussing our main results, it is worth commenting on the levels of innovation and adoption of technology derived from the Malmquist productivity index. Table B2 in Appendix B shows the percentage mean levels of innovation and adoption of technology for the 45 countries in our SSA sample. The overall mean estimates over the period shows a decline of 0.08% for innovation and a moderate increase of 1.7% for the adoption of technology. Overall, with the exception of Cape Verde, Mauritius and South Africa that had marginal increases of around 1 percent in innovation, 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. Countries like Liberia, Guinea Bissau, Sierra Leone, Niger and Malawi experience massive decline in innovation. Liberia and Guinea Bissau experience a decline of about 0.7%. Although the Malmquist productivity index does not explain the variations in innovation and adoption of technology, it is possible that these results largely reflect the democratic regime, quality of institutions, policy syndromes, the level of human resource development coupled with the level of investment in R & D in SSA countries. For instance, unlike the countries that experienced significant decline in innovation over the period, a country like Mauritius (widely held an African success story) which experienced a marginal increase in innovation and had the highest increase in adoption of technology over the period has constantly enjoyed democracy for the last 40 years and also had a better human capital level than other nations in SSA. With better governance and solid institutional framework put in place, they were able to implement an incredibly successful heterodox trade liberalisation policy to attract foreign direct investment and gain access to the export market (see Sachs and Warner, 1997; Subramanian, 2009).

Table 1
Summary Statistics and Correlation between Variables.

Summary statistics

Variables	Mean	Std. Deviation	Min	Max
Log Real GDP	11.60512	1.69598	8.22826	13.13625
Log Capital stock	10.88585	2.84085	2.47094	15.25389
Log Labour force	15.34888	1.51271	11.99462	20.46190
Innovation % (technical change)	−.08444	.14811	−.73845	.10859
Adoption of technology % (efficiency change)	1.77777	.89820	.13410	3.91717
Human capital (BL)	4.66148	2.12859	0.61500	10.56600

Correlation between variables

	Log Real GDP	Log Capital Stock	Log Labour Force	Innovation	Adoption of Technology	Human Capital
Log Real GDP	1					
Log Capital Stock	0.6706	1				
Log Labour Force	0.4921	0.5024	1			
Innovation	0.3241	0.4221	0.1102	1		
Adoption of Technology	0.4216	0.5981	0.5119	0.2201	1	
Human Capital	0.3807	0.2815	0.3253	0.1147	0.5315	1

We turn our attention to the results obtained from estimating Eq. (1). To make the discussion easier to follow we start by presenting the results (for each of our dependent variables) with BL as our proxy for human capital. The results related to innovation and adoptions of technology are portrayed respectively by Tables 2 and 3. In Tables 2 and 3, the results in columns (1) and (2); columns (3) and (4); and columns (5) and (6) portray the model using the pooled OLS, EIV and SYS GMM respectively.

The results in Table 2 show that the effect of human capital on innovation is positive but not consistently significant in all the specifications. Although, the baseline regression (column 1) shows that the effect of human capital on innovation is positive and significant, the effect of human capital becomes statistically insignificant when the control variables are introduced (column 2). The insignificant effect of human capital on innovations remains the same when we account for endogeneity of some of the right hand side variables using the instrumental variables techniques (see columns 3, 4, 5 and 6). These results suggest that the contribution of human capital to innovation in SSA is not significant. Therefore, the decline in innovation in SSA over the period (mean of about -0.08%) may be attributed to the lack of substantial effect of human capital on innovation.

The reported results in Table 3 also show overall, that human capital exerts a positive and statistically significant effect on adoption of technology. The baseline regression shows that the effect of human capital on adoption of technology is positive and statistically significant (column 1). The effect remains positive and statistically significant when the control variables are added (column 2). The subsequent estimation results using the instrumental variables approach (columns 3, 4, 5 and 6) also indicate a positive and significant effect of human capital on adoption of technology. The results sufficiently show that human capital plays a momentous role in the improvements in adoption of technology experienced by SSA countries as per the findings on the levels of adoption of technology (mean of around 1.7%).

Juxtaposing the existing literature with our results shows that the non-significance of human capital in boosting innovation (which is a relatively more skilled activity than adoption of technology) may be attributed to the lower levels of tertiary education in SSA (see Benhabib and Spiegel, 2005; Vandenbussche et al., 2006). As indicated earlier, the current levels of educational attainment is dominated by primary education. The tertiary component is much lower than that of the primary educational attainments. Tertiary educational attainment is lagging abysmally behind the developed and the emerging economies. The tertiary enrolment rate in SSA in 5% compared to 21% in East Asia. Arguably, this has an effect on the skills or level of human capital in SSA. This is evidenced by very low scientific and technical journals published (representing 0.06% of the world total); number of royalties

Table 2
Estimated results, Innovation and Human capital.

	Pooled OLS		EIV		SYS- GMM	
	(1)	(2)	(3)	(4)	(5)	(6)
Human capital (BL)	0.00256*	0.00761	0.000617	0.000729	0.00315	0.0513
	(0.00153)	(0.0102)	(0.00161)	(0.0141)	(0.00483)	(0.0626)
Log of population		− 0.00481		− 0.00146		− 0.00244
		(0.00812)		(0.00917)		(0.00216)
Openness		0.0209**		0.00525***		0.0387
		(0.00949)		(0.00180)		(0.0839)
Govt consumption (% of GDP)		− 0.00385*		− 0.00446**		− 0.00124**
		(0.00208)		(0.00201)		(0.000581)
Inflation		− 0.0136		− 0.0187		− 0.00517
		(0.0323)		(0.0379)		(0.00454)
Polity		− 0.00428		− 0.00144		0.0992
		(0.00927)		(0.000939)		(0.1680)
Constant	0.969***	0.929***	− 0.0261	0.989***	− 0.0433	0.903**
	(0.0128)	(0.0401)	(0.0166)	(0.0262)	(0.0490)	(0.386)
R-squared	0.323	0.522	0.344	0.471		
AR(1)					0.057	0.018
AR(2)					0.617	0.834
Sargan/Hansen p-value			0.8373	0.5699	0.401	0.740

Note: (1) Robust standard errors in parenthesis. (2) Time dummies included in all regressions. (3) *, **, *** represent, respectively, statistical significance at 10, 5 and 1 percent levels.

and licenses received (also representing 0.06% of the world total); and number of patent applications received by SSA residents (which is 0.00% of the world total) (WDI, 2009). However, the quality of available human capital (largely made of people with primary education and unskilled) seems to moderately support the adoption of technology on the continent. This is consistent with the postulation by Vandenbussche et al. (2006). Given the importance of innovation for development, the study clearly shows that STI policy options must focus on developing the quality of human capital in SSA in order to achieve technological progress, growth and development.

5. Conclusions and implications

Using data for 45 SSA countries from 1960 to 2010, this paper utilised the Malmquist productivity index approach to compute innovation and adoption of technology, and further examined the effects of human capital in explaining innovation and technology adoption in SSA. On one hand, the study indicates that the overall mean estimates over the period shows a decline of 0.08% for innovation and a moderate increase of 1.7% for the adoption of technology. Almost all the countries in the SSA sample experienced technical regress or decline in innovation, but the estimates for all countries showed an improvement in efficiency change or adoption of technology.

On the other hand, human capital appears to exert a positive and statistically significant impact on efficiency change (adoption of technology) whilst, its effect on innovation (technical change) is found to be insignificant. Our analyses revealed that human capital plays a substantial role in the increasing levels of adoption of technology experienced by SSA countries. The findings corroborate the evidence that young men and women in SSA (with some level of education) are showing a keen propensity for absorbing and adopting new technologies.

This study makes significant contributions to the scanty literature on innovation and adoption of technology in SSA, a region that has been under-represented in the existing literature. The study therefore provides valuable insights on the role of human capital in understanding the low levels of innovation and moderate adoption of technology in SSA. From public policy perspective, the study indicates

Table 3
Estimated results, Adoption of technology and Human capital.

	Pooled OLS		EIV		SYS-GMM	
	(1)	(2)	(3)	(4)	(5)	(6)
Human capital(BL)	0.00364*	0.00526**	0.00373*	0.00655***	0.00894*	0.00896***
	(0.00189)	(0.00212)	(0.00208)	(0.00231)	(0.00516)	(0.00205)
Log of population		− 0.00655*		− 0.00751*		− 0.00247
		(0.00368)		(0.00411)		(0.00293)
Openness		− 0.0173**		− 0.0199*		− 0.00378
		(0.00709)		(0.0104)		(0.00299)
Govt consumption (% of GDP)		− 0.0727***		− 0.0727***		− 0.00989**
		(0.0204)		(0.0206)		(0.00455)
Inflation		0.0139		0.0336		0.199**
		(0.0234)		(0.0299)		(0.091)
Polity		0.000514		0.000622		0.00171
		(0.00196)		(0.00145)		(0.00234)
Constant	1.016***	1.092***	1.012***	1.109***	0.999***	0.0341
	(0.00651)	(0.0218)	(0.00731)	(0.0487)	(0.0140)	(0.0386)
R-squared	0.1509	0.2671	0.104	0.277		
AR(1)					0.007	0.048
AR(2)					0.145	0.129
Sargan/ Hansen p –value			0.4246	0.2508	0.134	0.687

Note: (1) Robust standard errors in parenthesis. (2) Time dummies included in all regressions. (3) *, **, *** represent, respectively, statistical significance at 10, 5 and 1 percent levels.

that the nucleus of young men and women who are absorbing and adopting new technologies in SSA needs to be vigorously expanded by scaling up investments in particularly tertiary education (to boost tertiary enrolment rates and produce educated skilled labour force), and requisite soft and hard infrastructure such as high quality laboratories and scientific equipment among others. In addition, continual investments in education particularly in science, technology, and engineering among others would build up competence of the youth for innovation. The knowledge of the skilled youth would combine with existing technology to generate new knowledge, bridging the innovation gap and providing the impetus needed for the growth and development of the continent. To also revive deteriorating economies on the continent, investment in training and education can offer nations opportunity to lay the foundation for long-term growth.

The scope of the study is limited to innovation and adoption of technology at the cross country level. Therefore, the study does not analyse innovation and adoption of technology in detail at the specific country level. Given, the importance of this subject matter further investigation can be carried out at the country level in SSA. An in-depth case study related to a specific country on this subject can be done at the sectoral (agriculture, industry, service etc.) or cross sectoral level, and sub sectoral levels as well. Studies at these levels in tandem with the cross country analysis undertaken in this study would throw more light on explaining innovation and adoption of technology in SSA.

Appendix A

A.1. 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 Rao and Coelli (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.

A.1.1. 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.[2] 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.[3]

A.1.2. 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,

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

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

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

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.[4]

A.1.3. 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:

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

where

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

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

[3] 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.

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

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
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.

A.1.4. 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. Eq. (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 Eq. (A5) is a measure of technical change.

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

Appendix B

Table B1
List of countries.

Asia		
China	Singapore	India
Indonesia	South Korea	Pakistan
Malaysia	Taiwan	Sri Lanka
Philippines	Thailand	
OECD		
Australia	Finland	Netherlands
Austria	France	Norway
Belgium	Great Britain	New Zealand
Canada	Greece	Portugal
Switzerland	Ireland	Sweden
Germany	Iceland	United States
Denmark	Italy	
Spain	Japan	
Sub-Saharan Africa		
Angola	Guinea	Rwanda
Burundi	Gambia	Sudan
Benin	Guinea-Bissau	Senegal
Burkina Faso	Equatorial Guinea	Sierra Leone
Botswana	Kenya	Sao Tome and Principe
Central African Republic	Liberia	Swaziland
Côte d'Ivoire	Lesotho	Chad
Cameroon	Madagascar	Togo
Dem. Rep. of the Congo	Mali	United Republic of Tanzania
Congo	Mozambique	Uganda
Comoros	Mauritania	South Africa
Cape Verde	Mauritius	Zambia
Djibouti	Malawi	Zimbabwe
Ethiopia	Namibia	
Gabon	Niger	
Ghana	Nigeria	
Others		

Algeria
Egypt
Iran
Israel
Jordan
Morocco
Tunisia

Table B2
Total mean years of schooling and composition.

	Mean yrs of sch.	Mean yrs of sch_prim	Mean yrs of sch_sec	Mean yrs of sch_tert
Advanced economies				
Obs.	312	312	312	312
Mean	8.238103	5.172227	2.674467	.3914071
Std. Dev.	2.424502	1.20907	1.416781	.3057125
Min	1.1149	.8531	.2369	.025
Max	12.7056	7.7464	7.4761	1.5163
Europe and Central Asia				
Obs.	260	260	260	260
Mean	7.794357	5.135319	2.392546	.2664892
Std. Dev.	2.150996	1.773816	1.482455	.1906399
Min	2.6505	1.7376	.2735	.0217
Max	12.7488	8.8338	5.7922	1.2638
South Asia				
Obs.	91	91	91	91
Mean	3.12338	2.104929	.956078	.0623714
Std. Dev.	2.138676	1.532943	.7159511	.0600263
Min	.111	.0634	.0455	.0021
Max	8.4491	5.7308	2.9382	.2648
East Asia and the pacific				
Obs.	247	247	247	247
Mean	5.459552	3.666535	1.624765	.1682559
Std. Dev.	2.619628	1.422042	1.278148	.2092237
Min	.5077	.3737	.0807	.001
Max	11.8479	6.9846	4.947	1.1264
Latin America and the Caribbean				
Obs.	325	325	325	325
Mean	5.586006	4.010539	1.402042	.1734212
Std. Dev.	2.348657	1.471613	.9581855	.1616433
Min	.5936	.463	.1253	.0053
Max	10.5936	7.3306	4.4343	.7459
Sub-Saharan Africa				
Obs.	429	429	429	429
Mean	3.024273	2.286679	.6995026	.0380837
Std. Dev.	2.154743	1.507764	.7482915	.0512043
Min	.1478	.1389	.0079	0
Max	9.582	6.2995	3.3088	.4441
Middle East and North Africa				
Obs.	234	234	234	234
Mean	4.365068	2.654023	1.513837	.1972026
Std. Dev.	2.93087	1.6545	1.183707	.2024381
Min	.0114	.0114	0	0
Max	11.325	6.3962	4.1902	1.0377

Source: Barro and Lee (2010).

Table B3
Mean levels of innovation and adoption of technology %, 1960–2010 for SSA countries in the sample.

Country	Technical change (innovation)%	Efficiency change (adoption of Technology)%
Angola	− 0.03	2.2
Burundi	− 0.08	0.2
Benin	− 0.09	1.5
Burkina Faso	− 0.05	2.2
Botswana	− 0.01	3.5
Central African Republic	− 0.08	0.1
Côte d'Ivoire	− 0.01	2.4
Cameroon	− 0.04	2.1
Dem. Rep. of the Congo	− 0.08	1.5
Congo	− 0.09	2.2
Comoros	− 0.09	1.4
Cape Verde	0.1	3.3
Djibouti	− 0.05	0.8
Ethiopia	− 0.04	1.2
Gabon	− 0.03	0.4
Ghana	− 0.02	2.3
Guinea	− 0.06	1.2
Gambia	− 0.05	2.3
Guinea-Bissau	− 0.7	0.2
Equatorial Guinea	− 0.04	3.4
Kenya	− 0.01	2.5
Liberia	− 0.73	0.6
Lesotho	− 0.12	1.5
Madagascar	− 0.09	1.1
Mali	− 0.06	1.9
Mozambique	− 0.09	2.3
Mauritania	− 0.12	1.5
Mauritius	0.1	3.9
Malawi	− 0.21	1.8
Namibia	− 0.03	1.4
Niger	− 0.14	1.2
Nigeria	− 0.08	1.3
Rwanda	− 0.04	2.7
Sudan	− 0.1	1.3
Senegal	− 0.02	1.8
Sierra Leone	− 0.11	1.3
Sao Tome and Principe	− 0.02	2
Swaziland	− 0.08	0.9
Chad	− 0.05	1.8
Togo	− 0.06	1.4
United Republic of Tanzania	− 0.01	2.3
Uganda	− 0.09	2
South Africa	0.06	3.7
Zambia	− 0.07	1.5
Zimbabwe	− 0.09	1.9
Mean	**− 0.08**	**1.78**

Source: Authors' own calculations.

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