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

Abstract

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 remains limited. Using a sample of 45 sub-Saharan African countries from 1960 and 2010, we measure effects of human capital on innovation and technology adoption using the Malmquist index approach. The study uncovers that the overall mean estimates over the period shows a decline of 0.8% 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.

Keywords: Innovation; adoption of technology; human capital; Sub-Saharan Africa.

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 (Aghion and Howitt, 1992; Nelson and Phelps, 1966; Romer, 1990a). 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 & Suarez, 2012; Galang, 2012) as well as facilitating the technology catch-up in the 21st century (Lee, 2013; see also Zhang & Zhou, 2016). The existing body of research on the relationship between human capital and innovation has concentrated mainly on a more stable and well-developed institutional environment. Accordingly, it remains clear whether these findings will hold in an underdeveloped institutional environment, where the "rules of the game" are often uncertain (North, 1990; see Radjou, Prabhu and Ahuja, 2012; George, McGahan and Prabhu, 2012).

Despite these important streams of research, our understanding of how human capital enhances innovations and technology adoption in underdeveloped institutional setting 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 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 in innovation and adoption of technology.

This study offers several contributions to human capital and innovation literatures. First, we deviate from much of the existing literature on the relationship between human capital and innovation that has focused on mainly single country (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 develop and aid poverty alleviation efforts in the developing world (Amankwah-Amoah, 2016a; Clark and Frost, 2016; see also Kaplinsky et al., 2009). In addition, our study contributes to the literatures technology adoption (Lanzolla and Suarez, 2012), human capital theory (Becker, 1964; Schultz, 1961) and innovation (Etzkowitz & Leydesdorff, 2000) by deepening our understanding of how human capital can enhance innovation and facilitate technology adoption. Moreover, the study adds further evidence to growing streams of research that have hinted that quality of human capital, ability to develop, leverage and utilise might be the most important factors in explaining the effects of human capital rather than the mere possession of human capital by a nation or firm (see Sirmon, Hitt and Ireland, 2007; Sirmon, Hitt, Ireland and Gilbert, 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 and innovation. 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) can provides a theoretical underpinning towards a better understanding of the role of individuals in enhancing innovation and adoption of technology. By human capital, we are referring to an individual's knowledge, skills and experiences, which can be utilised to foster innovation activity (Becker 1964; Schultz, 1961).

Past studies have indicated that human capital relates to firms' ability to develop and maintain their competitiveness (Youndt, Subramaniam and Snell, 2004; Ployhart and Moliterno, 2011; Ployhart, Van Iddekinge and MacKenzie, 2011). Firms' ability to develop business ideas and innovation has been found to be predicated on quality of human capital held by the employees (Deakins and Whittam, 2000). Similarly, governments' ability to initiate policy and ensure effective implementation is also predicated 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. Indeed, the new endogenous growth theories also describe the stock of human capital as the engine of growth through innovation (Aghion and Howitt, 1992; Romer, 1990a).

Nelson and Phelps (1966) argued that a more educated labour force would adopt new technologies faster. Some researchers' have also demonstrated 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 (see Benhabib and Spiegel, 1994, 2005; Barro and Sala-i-Martin, 1997; and Barro, 1999; Vandenbussche et al., 2006; Ang et al., 2011). In this direction, 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 to diffuse (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.

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 Krugman, 1994; Klenow and Rodriguez-Clare, 1997; Hall and Jones, 1999; Easterly and Levine, 2001; Jerzmanowski, 2007). 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, 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; and O'Connell and Ndulu, 2000, 2003; Danquah and Ouattara, 2014). 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

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; Kruger, 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 A1.

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:

$$\Delta \ln Y_{it} = \gamma_{0i} + \gamma_1 \ln H_{it} + \xi Z_{it} + \gamma_t + \varepsilon_{it} \qquad (1)$$

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.

The panel data set contains repeated observations over time for 45 SSA countries. Equation (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 equation (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).

Based on the theoretical and empirical discussions, we expect the sign of the estimated coefficient of human capital to be positive across innovation and adoption of technology.

Data 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 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. Using the perpetual inventory method with a revised depreciation rate of 0.05 percent we extend the dataset to 2010[2].

For the total human capital variable, we use Barro and Lee (2010), henceforth 'BL', dataset on total human capital and human capital compositions. This new dataset exploits new sources of

[1] For all our SYS- GMM results we used the small sample bias correction following Windmeijer (2005).
[2] 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.

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 and (considering SSA region as a whole), 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.

We introduce 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 (2012); openness (measured as the ratio of exports plus imports to GDP), derived from the Penn World Table 8.1; and the quality of institutions and democracy obtained from Marshall and Jaggers, (2009, Polity IV Project).[3] The descriptive statistics of these variables are shown in appendix B, table (B2).

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 1 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 0.8% for innovation and a moderate increase of 1.7% for the adoption of technology. Overall, with the exception Cape Verde, Mauritius and South Africa that had marginal increases of around 1 percent in innovation,

[3] 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).

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.

[Please insert Table 1, 2, 3 here]

5. Conclusions and Implications

Using data for 45 SSA countries from 1960 to 2010, this paper examined the effects of human capital in explaining innovation and technology adoption. On one hand, the study indicates that the overall mean estimates over the period shows a decline of 0.8% for innovation and a moderate increase of 1.7% for the adoption of technology. In addition, all 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 additionally 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.

From public policy perspective, the study indicates that the nucleus of young men and women who are absorbing and adopting new technologies needs to be vigorously expanded by scaling up investments in education (to provide a large university –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 foundation for long-term growth.

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Table 1: 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

We 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 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. 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 -0.8%) may be attributed to the lack of substantial effect of human capital on innovation.

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		-0.00385*		-0.00446**		-0.00124**
(% of GDP)						
		(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.

The reported results also show overall, that human capital exerts a positive and statistically significant effect 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%). This finding is also consistent with Vandenbussche et al. (2006) hypothesis which suggests that the adoption of technology involves mostly physical capital.

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

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.[4] 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.[5]

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.

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

[5] 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.

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,

$$P(x) = \{y : x \, can \, produce \, y\}. \qquad \text{(A1)}$$

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

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

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.[6]

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.

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

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:

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

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

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

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

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

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

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 (see Färe et al., 1994).

Appendix B

Table (B1): List of Countries

Asia		
China	Singapore	India
Indonesia	South Korea	Pakistan
Malaysia	Taiwan	Sri Lanka
Phillipines	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): 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)	-.82467	.0530567	-.73845	.10859
Adoption of technology% (Efficiency change)	1.78162	.0486575	.13410	3.91717
Human capital (BL)	4.66148	2.12859	0.61500	10.56600