Innovation, Technology Diffusion and Poverty Traps: The Role of Valuable Skills

George Messinis and Abdullahi D. Ahmed
Centre for Strategic Economic Studies

Working Paper No. 47
Centre for Strategic Economic Studies
Victoria University
Melbourne

March 2010

PO Box 14428
Melbourne VIC 8001 Australia
Telephone +613 9919 1340
Fax +613 9919 1350
Contact: george.messinis@vu.edu.au

Innovation, technology diffusion and poverty traps: The role of valuable skills[†]

George Messinis[††] and Abdullahi D. Ahmed

Centre for Strategic Economic Studies,

Victoria University, Australia

March 2010

Abstract

This paper develops a new index of human capital that measures cognitive skills employed by the adult population in seventy nations during 1970-2003. The index is compared to existing measures of human capital in the Benhabib and Spiegel (2005) model. Analysis goes beyond the Cobb-Douglas production function. The evidence shows that (i) the new index best explains trends in technology growth; (ii) the skills-education deficit has increased in Africa and advanced OECD countries; (iii) the number of countries in poverty traps has risen; and (iv) valuable skills impact most on innovation when physical capital and skills are complementary. The results suggest that public policy ought to pay more attention to the employability of skills.

Keywords: Skills; Human capital; Growth; Innovation; Diffusion; Poverty Traps

JEL Classification: I2, O1, O3, O4

---

† We have benefited from comments provided by an associate editor, anonymous referees, and participants at the *2nd International Conference on Educational Economics,* in Athens in 2008, and seminars at La Trobe University, University of Queensland, University of New South Wales, and Victoria University. Any remaining errors are our responsibility.

†† Corresponding author: CSES, Victoria University, P.O. Box 14428 Melbourne, Vic. 8001 Australia. Tel.: +61399191330, E-mail address: george.messinis@vu.edu.au.

1. Introduction

Economic theory considers human capital[1] to be the engine of economic growth.[2] Several hypotheses have been proposed to explain the role of human capital. Nelson (2005) has condensed these into two schools of thought: accumulation theories and assimilation theories. The first envisage a direct effect of human capital on labour productivity as an explicit factor of production embodied in *effective* labour. This approach suggests that it is new investment in human capital that matters for growth. In contrast, the second school of thought explores the relation between the level of human capital and total factor productivity growth or technological change; the emphasis here is on the link between human capital and disembodied knowledge as manifested in technology. The former school highlights the role of human capital accumulation when it is the stock of human capital that is important in the latter; what Dowrick (2003) calls *growth effects* and *level effects* respectively.

The second school of thought has emerged as a synthesis of two ideas. One is that greater understanding of the role knowledge and skills play can shed light on the process of technology growth. This draws on earlier insights on the link between R&D, innovation and market value in Schumpeter (1934) and Griliches (1981) and is central in models of endogeneous growth highlighting the role of innovation and sustainable growth (Romer 1990; Aghion and Howitt 1998). Human capital is also a key driver of sustained technological progress in unified growth theory (Galor and Weil, 2000; and Galor, 2005).

The second idea highlights knowledge externalities as the source of spillovers from technology leaders to less developed countries. However, the adoption of foreign technology depends on the 'absorptive capacity' of the imitator (Wolff, 2001; Falvey *et al.* 2007). Human capital is a key determinant of absorptive capacity since it enables workers to understand and assimilate new technology; a particular formulation of the convergence process whereby less developed economies catch-up with the developed world.[3] The idea originates in Nelson and Phelps (1966) who

[1] As a concept, human capital has been defined as the 'knowledge, skills, competencies and other attributes' that are relevant to economic activity (OECD, 1998).

[2] See Nelson and Phelps (1966), Aghion and Howitt (1998), Barro (2002), Galor (2005), Nelson (2005), Hanushek and Wößmann (2007), and Ehrlich (2007).

[3] The literature of 'international spillovers' have also considered FDI and trade as channels of knowledge transfer (Coe and Helpman, 1995 and Acharya and Keller, 2007).

assessed education to be a catalyst in the diffusion of new technologies. Their model rests on two key assumptions: the further away an economy is from the technology frontier, the greater the potential rate of catching up; and the larger the human capital the bigger is the capability to learn and adopt the new technology.

Benhabib and Spiegel (1994) integrate the two ideas in a generalised model that attempts to explain both innovation and technology diffusion. The model builds on the intuition that the two views of human capital are complementary, for they explain different stages of economic development; i.e., nations closer to the technology frontier have accumulated high levels of human capital that could support innovation while countries far from the frontier focus on technology diffusion.[4]

Although intuitively appealing, the original Nelson-Phelps hypothesis, suggests that the imitation of foreign technology is always beneficial since workers can 'follow and understand new technological developments' (Nelson and Phelps 1966, p.69). Moreover, the hypothesis implies that a backward economy could develop rapidly by simply relying on human capital and imitation. As acknowledged by Benhabib and Spiegel (2005), this seems to ignore barriers to free-riding and absorption of new technology. In particular, it contradicts Schumpeter (1934) and economic intuition that emphasise the role of intellectual property rights.

New evidence in the 1990s motivated further progress in assimilationist theory. First, rather than factor accumulation, it was the Solow 'residual' or total factor productivity (hereafter TFP) that explained most of the cross-country differences in growth rates. Second, per capita incomes for a number of countries seemed to diverge rather than converge.[5] Third, substantial investment in education failed to insulate less developed countries (LDCs) from stagnation (Pritchett, 2001). In order to account for the above limitations, Benhabib and Spiegel (2005) extend the Nelson-Phelps model[6] by considering a logistic diffusion process that allows for impediments to imitation and divergence in world income. In a cross-sectional empirical application, the authors find the logistic diffusion model to be superior to the exponential model of Benhabib and Spiegel (1994) in explaining world income growth patterns. Further, the authors identify a number of countries at risk of falling into poverty traps but this number appears to have diminished over time.

---

[4] This has been empirically confirmed by Vandenbussche, Aghion and Meghir (2006).

[5] As summarised in Temple (1999) and Easterly and Levine (2001).

[6] An alternative account of economic stagnation is Acemoglu, Aghion and Zilibotti (2002).

This paper contributes to the literature of technology diffusion on three levels. First, it departs from the standard focus on formal education to develop a new measure of human capital that incorporates several dimensions of human capital and emphasises the application of cognitive skills by the adult population that we call ‘valuable skills’. In brief, it extends Dagum and Slottje (2000) to estimate a latent index of human capital by utilising four new indicators: international test scores; scientific research output; book production, and trade in print media and information and communication technology. There are four main reasons as to why we focus on such a composite but single index of human capital: (a) human capital is too rich to be captured by a single dimension such as schooling (Lee*et al*., 2003; Dagum and Slottje, 2000); (b) rather than skills *per se*, it is employable skills that are valuable in economics (Schultz, 1961; Becker, 1964; Nelson, 2005), (c) it is important to assess how well the new index performs in comparison to competing single indicators, and (d) given the scarcity of valid instruments,[7] the latent factor approach minimises biases associated with endogeneity and measurement errors (Heckman *et al*., 2006).

Second, following Durlauf, Johnson and Temple (2005), we account for model uncertainty regarding the definition of human capital and the functional form of the production technology.[8] Thus, we run the new index in a horse race against competing measures of human capital to examine the Benhabib and Spiegel (2005) model. Further, we test the robustness of our results by relaxing the assumption of a Cobb-Douglas production function to consider two alternative forms: the constant-elasticity of substitution (CES) function of Duffy *et al.* (2004), and the translog production function of Papageorgiou and Chmeralova (2005). This is motivated by the literature on capital-skill complementarity (CSC) and skill-biased-technical-change (SBTC).

A third contribution is to examine the Benhabib and Spiegel (2005) model of logistic diffusion by empoying dynamic panel data econometrics for two main reasons. It seems intuitive to utilise available information on the time-series data generating processes of key variables explaining economic growth as a dynamic relation. Second, panel data estimation techniques are advantageous in finite cross-

[7] For further discussion of the issue, see Durlauf *et al*. (2005).

[8] By convention, the term ‘production technology’ refers to the form of the production function, in contrast to the term ‘technology’ that stands for total factor productivity, TFP.

sectional data when complemented with a methodology that minimises some of the limitations[9] associated with reverse causality and measurement errors.

The paper is structured as follows. Section two traces the evolution of technology diffusion theory and outlines three key models. Section three presents the new latent index of human capital. Section four reports on comparative dynamic panel data estimation results using alternative measures of human capital in the logistic diffusion model of Benhabib and Spiegel (2005). Section five conducts sensitivity analysis. Section six summarises the new evidence and concludes.

2. Knowledge Diffusion: Three Models

In general, theories of human capital and growth define output, *Y*, to be of the general functional form: $Y_{j,t} = F(A_{j,t}(H_{j,t}), X_{1j,t}, \ldots, X_{nj,t})$ where $Y_{j,t}$ is per capita output in country j in period t, A represents technology being a function of human capital, *H*, and $X_1, \ldots, X_n$ are n factors of production that may also include *H*.

Assimilationist theories focus on A. Here, we outline three models of technology diffusion with a Cobb-Douglas production function, as first proposed. For brevity, we drop the country indicator that is implicit. We begin with the Benhabib and Spiegel (1994) model with the production function:

$$Y_t = A_0 K_t^{\alpha} L_t^{\beta} \varepsilon_t \tag{1}$$

where A_0, *K*, *L* and ε represent initial technology, physical capital, labour and an error term respectively. Note that technology cannot be seen independently of human capital (i.e., the idea of human capital being the ‘engine of growth’ in endogeneous growth theory). Combining the role of human capital and technological development – where a country’s level of human capital enhances absorption of its own and foreign technology – Benhabib and Spiegel (1994) specify technological progress, Δa, as:

$$\Delta a_t = gh_t + mh_t\left[\frac{A_t^{\max} - A_t}{A_t}\right] = (g-m)h_t + mh_t\left[\frac{A_t^{\max}}{A_t}\right] + \varepsilon_t \tag{2}$$

[9] For a thorough review of growth econometrics, see Durlauf *et al.* (2005).

Here, h_t is the natural logarithm of H_t, and g, m >0.[10] In this equation, the first term represents domestic innovation and the second term is the Nelson and Phelps (1966) idea of technological diffusion being the product of a country's level of human capital and the 'distance to the frontier' (i.e., the gap between the technological level of a leading country, A_t^{max}, and that of the home country, A_t). Note also, *g* is the effect of human capital on innovation while *m* captures 'absorptive capacity'.

Taking logs of equation (2) can show that the model predicts that economic growth will also depend on the stock of human capital and the distance to the frontier. Note, technology diffusion is an exponential process; i.e., countries further away from the frontier catch-up faster than those closer, and any country in some distance from the frontier could specialise in imitation without any R&D effort (Jones, 2008). Further, the model also implies that imitation could be more beneficial than innovation for countries closer to the frontier, as long as the distance to the frontier is greater than (g-m)/m.

Benhabib and Spiegel (2005) revise (2) to propose a logistic model of diffusion. They acknowledge the potential for poverty traps due to barriers to assimilation of foreign technology. Logistic diffusion again emphasises the interaction of human capital and the technology gap except that the rate of adoption of foreign technology is further moderated by the inverse of the distance to the frontier[11] due to technology clusters or an incompatibility with domestic technology or social values (Rogers, 2005). More formerly, logistic diffusion takes the following form[12]:

$$\Delta a_t = gh_t + mh_t \left[\frac{A_t^{\max} - A_t}{A_t} \right] \left[\frac{A_t}{A_t^{\max}} \right] = (g+m)h_t - mh_t \left[\frac{A_t}{A_t^{\max}} \right] + e_t \qquad (3)$$

Compared to the exponential model in (2), diffusion in (3) is moderated by the inverse of the distance to the frontier, also known as 'backwardness', (A/A^{max}). As a

[10] Benhabib and Spiegel (1994) specify H_t instead of h_t and then equate H_t with educational attainment. We draw on Krueger and Lindahl (2001) and adopt the Mincer approach to specifying human capital as an exponential function of schooling. The end result is the same since in this study it is h_t that equates with educational attainment in all three models.

[11] All three theoretical models take the USA to be the technology leader.

[12] $\Delta a = (g + \frac{c}{s})h_t - \frac{c}{s} h_t (A_t / A_t^{\max})^s$ is the more generalised model proposed by Benhabib and Spiegel (2005). It nests two limiting cases: the exponential diffusion model of Benhabib and Spiegel (1994) when s=-1, and the logistic model when and s=1. On the basis of the evidence in Benhabib and Spiegel (2005), this study considers only these two scenarios.

result, the innovation effect of human capital is relatively larger and the catch-up process is slower when the country is very far or very close to the frontier.

3. Human Capital as Valuable Skills: A New Index

3.1 Background

Benhabib and Spiegel (2005, 1994) and Dowrick and Rogers (2002) abstract from measurement issues and utilise quantitative measures of human capital; educational attainment and school enrolments respectively. However, these measures are highly problematic in international studies for several reasons.[13] First, they are poor indicators of education quality. Second, they ignore factors other than formal education that impact on skill formation, and fail to measure the level of skills that are actually employed at the workplace.[14] Last but not least important, they often evolve in correlation with other macroeconomic variables that introduces endogeneity biases in estimation.

Hanushek and Kimko (2000) depart from quantitative measures of education to jointly consider quantitative and qualitative indicators in growth equations. They find that international test scores of student achievement in mathematics and science, TIMSS, are significant predictors of growth. Coulombe *et al.* (2004) and Hanushek and Wößmann (2007) have confirmed a link between test scores and economic performance. Hanushek and Wößmann (2007) argue that the cognitive skills-eduction deficit is greater in developing countries[15] and quality indicators are less susceptible to estimation problems such as endogeneity, although recent evidence suggests that selection and endogeneity biases remain (Glewwe, 2002; Paxson and Schady, 2007).[16] Similarly, Jones and Schneider (2006) and Jones (2008) focus on IQ test scores as a better measure of cognitive skills and abilities.

---

[13] For a review of measurement errors in the estimation of educational attainment, see Cohen and Soto (2007). This literature is beyond the scope of this study.

[14] These problems have been well documented in Bils and Klenow (2000), Wößmann (2003), Le *et al*. (2003), Abowd *et al.* (2005), and Joss (2001).

[15] An early but brief observation of the skills deficit in developing countries was by Tsoukalas (1976). His data clearly show that less developed Southern European countries in 1960 had markedly lower rates of tertiary student enrolments in applied sciences and technology than the more advanced OECD economies.

[16] Lévy-Garboua et al. (2004) challenge the idea that test scores are good indicators of human capital. They call for a return to the notion of 'market value of school outputs'.

The search for multi-dimensional measures of human capital has advanced to new directions. One involves the relaxation of the Nelson and Phelps (1966) assumption that all education is useful for technology diffusion. Thus, Acemoglu, Aghion and Zilibotti (2002), Ciccone and Papaioannou (2005), and Vandenbussche *et al*. (2006) decompose education and suggest that primary or secondary education is more suitable for adoption while higher education is best for innovation.[17]

An alternative account of multi-dimensionality invokes the Mincerian approach to human capital that seeks to decipher two key insights. One is that human capital is a composite index of cognitive skills acquired at school, and the net effect of work experience, training and skill depreciation. Moreover, the current market value of these skills can vary over time and across nations.[18] Although this micro approach focuses on *private* returns to skills, this methodology is employed here at the macro-level to account for both cognitive skills and the application of skills.

Aristotle (1976), Dewey (1916) and Bourdieu (1977) all emphasised the view that knowledge is a social product generated within contexts of experience. More recent developments in biology, sociology and anthropology closely associate knowledge with 'evolving skills' being generated in the process of people's engagement in the ordinary business of life (Ingold, 2000). The potential discrepancy between education and knowledge has been emphasised in various forms and fields. One expression is Sen's (1997) distinction between 'human capital' and 'human capability' where the latter emphasises 'functionings' (i.e., outcomes and achievements) that enable people to participate in markets and adapt to change (Lanzi, 2007). Another is the 'knowing-doing gap' that Joss (2001) describes as the 'ability to implement what is known' and not abstract knowledge. The innovation literature also pays attention to a balance between the 'body of practice' and the 'body of understanding' as key to explaining knowledge transfer (Nelson, 2005). Finally, the gap between schooling and skills is implicit in the emerging literature of job training (Borghans and Heijke, 2005; Nordman and Wolff, 2007; Destre *et al*., 2008; Robst, 2007).

[17] Hanushek and Wößmann (2007) and the skill decomposition approaches are two interpretations of why education failed to stimulate growth in LDCs (Pritchett 2001). The latter approach suggests that a single indicator of human may be limiting when assessing the human capital-diffusion nexus.

[18] This is the approach adopted by Krueger and Lindahl (2001) and Abowd *et al.* (2005). See Sianesi and van Reenen (2003) for a comprehensive survey of alternative methodologies in the measurement of human capital.

3.2 A New Human Capital Index

In this section, we explore the idea that human capital is a composite index that jointly accounts for the following key dimensions of human capital: cognitive skills acquired at school, cognitive skills that are useful in scientific research, and cognitive skills applied by the working population that are useful in the application of modern technology. We insist on a single summary measure for its capacity to facilitate comparisons with other existing measures of human capital. Hence, we account for the multi-dimensionality of human capital only with respect to the construction of a new composite index that incorporates several dimensions of human capital.[19]

The search for a new human capital index as a latent unobservable factor seems warranted when we re-consider Schultz' (1961) emphasis on 'knowledge and skills that have economic value' in the light of (a) heterogeneity and time-varying returns to education (Psacharopoulos and Patrinos, 2004; Hartog and Oosterbeek, 2007); (b) non-cognitive skills (Heckman *et al*., 2006); (c) skill obsolescence (Alders, 2005; Gorlich and de Grip, 2007), and (d) skill-job mismatch and overeducation (Cheng and Ghulam, 2007; Korpi and Tahlin, 2007). Further, several studies have proposed the latent factor estimation approach as an effective strategy in dealing with biases associated with measurement errors and endogeneity.[20]

We exploit new data not available to Hanushek and Kimko (2000) and Dagum and Slottje (2000) to estimate human capital as a latent factor that measures the level of skills acquired in secondary education that are employed by the adult population; we call this composite index 'valuable skills'. Hanushek and Kimko (2000) utilise international test scores in maths and science (TIMSS) to impute cross-section measures of cognitive skills, assuming that quality of schooling evolves slowly over time. Dagum and Slottje (2000) on the other hand estimate human capital as a latent variable using household survey data. However, these data fail as direct measures of intelligence or education quality (Le *et al*. 2003, p.293).

We employ a multiple-indicator model with one latent common factor, with $k=1,\ldots,n$ indicator for country j at time t is the common factor. The common factor is

[19] Ciccone and Papaioannou (2005) and Vandenbussche, Aghion and Meghir (2006) suggest that a single indicator of human may be limiting when assessing the impact of human capital on innovation and diffusion. Note, however, that these studies have utilised traditional measures of schooling.

[20] See, for instance, Temple (1999), Durlauf *et al*. (2005), and Heckman *et al*. (2006).

the unobserved characteristic of valuable skills that drives the *n* indicators. In search for appropriate indicators, we consider variables that proxy several dimensions of applied cognitive skills by the adult population. We select the following four series: imputed TIMSS scores lagged two periods, TS_{t-2}[21]; per capital scientific publications in science, SciP; per capita book publications in the field of pure and applied science, BOOKS, and trade in print media and ICT, T_ICT. The use of TIMSS as a proxy for cognitive skills has been established in the literature cited earlier. Yet, TIMSS scores measure skills by pupils in low secondary schools and would not necessarily summarise the skills of the labour force. Thus, we use estimates of TIMSS two 5-year periods earlier. It also seems intuitive that our bibliometrics measure, SciP, would reflect the quality of human capital. Gault (2005) argues that the process of knowledge creation - closely interlinked with technological progress - by academic scientist can be measured by academic publications. In a historical study of early modern Europe, Baten and van Zanden (2008) have proposed that book production is a powerful proxy for human capital since it summarises both literacy skills *and* market demand for books. In this study, we have utilised UNESCO data on non-periodical printed publications in the fields of pure and applied sciences. This is in order to measure technical skills that are more comparable to TS_{t-2} and SciP. However, SciP and BOOKS may be weak proxies of valuable skills if we account for key features of the global publishing industry: the focus on English-speaking; the spatial concentration in the UK and the USA; the rise of electronic publishing; and limits to universal copyright laws.[22] T_ICT controls for some of these limitations since it includes trade in books and ICT equipment that directly relates to publishing, printing, and data processing. The choice of T_ICT also rests on economic intuition of a link between trade and skilled human capital (Galor and Weil, 2000) or technology transfer (Apergis *et al*., 2009; Madsen, 2007). Here, however, we focus on trade as an indicator of the applicability of cognitive skills. The focus on the practise of cognitive skills by the adult population is one reason why we refrain from utilising quantitative measures of schooling in factor analysis; the principal objective of factor analysis is to closely identify skills rather than schooling in general.[23]

[21] For detailed data sources and definitions of all variables, see the Appendix.

[22] For a comprehensive review of the global publishing industry, see Feather (2003).

[23] Note, however, we employ measures of schooling in the imputation of TIMSS skills. For tranparency, however, we also utilise the Cohen and Soto (2007) estimates of years of education as an indicator in section four.

It is intuitive that TS_{t-2}, SciP and BOOKS contain information on cognitive skills while BOOKS and T_ICT provide information on the employability of skills. Thus, if a single common factor drives all five indicators, that factor is likely to measure cognitive skills that have economic value. Admittedly to the extent that the new single latent factor captures an effect other than human capital, our approach would be an imperfect measure of human capital. However, we maintain that the four indicators are highly relevant components of the human capital index targeted here.

Note, missing observations is a major limitation of existing data on TS_{t-2} and, to a less extend, BOOKS. Since TS_{t-2} is critical to our study, we impute test scores and splice two sets of imputed $TIMSS_t$ (in logs). The first is the expected value of $TIMSS_t$ with respect to a contemporaneous information set I_t, $E_t[TIMSS_t \mid I_t]$, where E_t is an expectations operator. The second is the expected value of $TIMSS_t$ with respect to the information set at time t+2, $E_{t+2}[TIMSS_t \mid I_{t+2}]$. We splice the two series at period three (i.e., 1980-84) and construct a composite series TS_{t-2} that equals $E_{t+2}[TIMSS_t \mid I_{t+2}]$ in the first two periods (i.e., 1970-79) and $E_{t-2}[TIMSS_{t-2} \mid I_{t-2}]$ (i.e., TIMSS lagged twice) in all other periods (i.e., 1980-2003). We consider the following variables in logs: secondary (SECO) and higher education (HIGH) attainment rates, average years of education (EDU), infant mortality rate (MoR), labour participation rate (LPR). The education variables are intended to capture the effect of parental and public education on student test performance. Infant mortality rates are used on the basis of a close link between mortality and education quality (Fortson, 2008; Jamison *et al*., 2007). Labour market participation also provides extra information on the opportunity to employ skills at the workplace and benefit from investment in education.

In addition, we use two indicator variables. 'D_miss' takes the value of one if three missing values of TIMSS are observed during the period 1980-1994 and zero otherwise. This is to control for unobservable factors that have impinged on the stock of human capital, such as famine or epidemics. 'D_East_Euro' is a regional dummy variable that controls for the absence of market signals in East European economies (Russia, Romania, Bulgaria, Slovakia, Poland and Hungary).[24]

Columns 1-2 in Table 1 present panel feasible Generalised Least Squares, GLS, estimation results that are robust to heteroskedasticity in the errors. These suggest that young students perform better in TIMSS tests when a higher proportion of the general

[24] We also considered per capita income as a predictor of TIMMS scores but it was not statistically significant.

population has attained secondary and post-secondary education. Students also benefit from greater labour force participation. However, higher infant mortality or more years of education have an adverse effect on student performance. The former seems intuitive while the latter alludes to a trade off between quantity and quality of education. Further, the results show that missing values associate with a deficit in human capital while pupils in transitional economies as a group seem to have performed relatively better.

In column three of Table 1, we impute BOOKS. In our information set, we include the log of per capital scientific publications in science (SciP) and a new series that measures the number of years at war due to an armed conflict (WAR); see Appendix for details. The results show that armed conflict and higher mortality rates impact adversely on the production of new books in science. Scientific articles, on the other hand, stimulate the production of new books since it is to be expected that BOOKS and SciP are complements. The estimates in Table 1 are used to impute TIMSS and BOOKS to construct TS_{t-2} and BKS respectively for all countries.

These imputed series are subsequently used together with SciP, and T_ICT to conduct principal component factor analysis. We allow for two time-varying latent factors. For economy of space, the results are not reported here but can are available on request. They can be summarised as follows. First, eigenvalues and model selection information criteria indicate the existence of a single factor.[25] Second, the factor loadings (i.e., the correlations between the indicator and the factor; assuming a single factor) are quite high and increase over time for TS_{t-2}, BKS and T_ICT. Third, the estimated factor scores suggest that all four indicators have similar weight on the latent factor with that of TS_{t-2} becoming relatively more important since 1970-74. We conclude that there exists a single latent index. Given that all four indicators proxy closely skills and, more importantly, the application of skills, we call this new index 'valuable skills', VS, being the weighted sum of the four indicators with the 'scores' as the weights.[26]

[25] That is, only the eigenvalue of the first factor is greater than 1.

[26] Following Krueger and Lindahl (2001), we run reliability tests comparing the new index in a horse race with the following alternatives: years of education by Barro and Lee (2001); the revised series of years of education by Cohen and Soto (2007), the imputed TS_{t-2}; and the cross-section IQ series of Lynn and Vanhanen (2002). Overall, the new 'valuable skills' index outperforms all alternatives and results are available on request.

Table 2 reports the new estimates for all countries and Figure 1 depicts the top and bottom twenty performers in terms of growth in the new index of human capital over the period 1970-74 to 2000-03. China, Indonesia, South Korea, Turkey and South European countries increased their valuable skills most while fourtheen of the twenty worse performers were African nations. Surprisingly, Sweden, Canada, and France were also part of the worse twenty performers.

Figure 2 compares the years of education measure of Barro and Lee (2001) to that of the new index of 'valuable skills', VS,[27] for six regional groups: OECD20 countries, South America, Asia (excluding Japan and South Korea), Africa, transitional economies in Europe and South Europe.[28] The results confirm Hanushek and Wößmann's (2007) finding of a 'skills deficit' in developing economies. That is, while formal education has surged in most regions, the the stock of valuable skills in Africa and East Europe has declined since the mid 1970s and has failed to improve in South America. More surprising, the new index increased during the 1970s but has declined sharply in OECD20 countries since the late 1980s. In addition, Asia and South Europe have witnessed the greatest gains in valuable skills over the whole period, although they remain behind the levels recorded in the OECD20.

3.3 Dynamic Panel Data Estimation

In this section, five alternative measures of human capital are utilised to test the logistic diffusion model of Benhabib and Spiegel (2005) in (3). In order to account for non-linear errors and the potential for endogeneity, we employ the *System GMM* panel estimator of Arellano and Bover (1995).[29] Although lagged variables are not a full proof strategy to control for endogeneity, we employ lags 2-3 to instrument both the human capital stock, h, and technology diffusion, $h(A/A^{max})$, the latter being in view of Acemoglu *et al*. (2002).

Below, we examine the performance of five alternative measures of human capital in assessing the empirical validity of the Benhabib and Spiegel (2005) model of

[27] Note, for comparability, all measures of human capital were rescaled into equivalent years of education using robust panel FGLS, givn Lane (2002).

[28] The OECD20 group comprises of Austria, Australia, Belgium, Canada, Denmark, Finland, France, Germany, Iceland, Ireland, Japan, Korea, Mexico, Netherlands, New Zealand, Norway, Sweden, Switzerland, UK and the USA. Italy, Greece, Portugal and Spain form the 'South Europe' group.

[29] We used a two-step robust estimation with a finite-sample correction (Windmeijer 2005).

logistic technology diffusion.[30] These measures are: average years of education by Barro and Lee (2001), EDU_BL; average years of education by Cohen and Soto (2007), EDU_CS; the original TIMSS series (TIMSS); the imputed lagged TIMSS series (TS_{t-2}), and the new latent index of valuable skills, VS.

Table 3 presents system panel GMM estimates of the Benhabib and Spiegel (2005) model. Note that the data reveal that USA is the technology leader.[31] Regressions (1)-(2) utilise the quantity measures of education, EDU_BL and EDU_CS, columns 3-4 use the cognitive skills measures, TIMSS and TS_{t-2}, and regression (3) utilises the new valuable skills measure, VS. The results indicate that only when TIMSS and VS are used as measures of human capital we obtain statistically significant coefficients that have the expected sign. Although limited observations for TIMSS make comparisons difficult, the estimated coefficient of *h* in regression (2) is implausibly large when compared to that of $h(A/A^{max})$.[32] In contrast, the estimated parameters in column (4) are reasonable. Table 4 also reports the Arellano-Bover AR(1) and AR(2) tests for autocorrelation, as well as the Hansen test of over-identifying restrictions. While the AR(1) is expected to be significant at 5% level, AR(2) is a specification test. In all regressions but (1), the AR(2) and Hansen statistics are not significant, the latter confirming the validity of the instruments used.

Benhabib and Spiegel (2005) also explore the implications of the logistic diffusion process for developing nations and their capacity to catch up with the developed economies. That capacity, they argue, depends on a critical threshold level of human capital. Nations with human capital levels below that threshold stagnate and remain behind for decades. They derive this threshold or ‘catch-up condition’ to be:

$$h_t^* = \exp\left(\frac{sg\ln(h_t^{max})}{sg+m}\right) \tag{4}$$

In the case of logistic diffusion, s=1, h_t^{max} is human capital in the leading country in period t, and *g* and *m* are estimates of the human capital stock and diffusion

[30] We have also compared the new index in two alternative models of technology diffusion: Benhabib and Spiegel (1994) and Dowrick and Rogers (2002). The estimation results clearly point to Benhabib and Spiegel (2005) as a superior model and are available upon request.

[31] We follow Benhabib and Spiegel (2005) to estimate the log of TFP or $\ln(A_t)$ as a residual by assuming $\alpha=(1/3)$ and $\beta=(2/3)$; i.e., $\ln(A_t) = \ln(Y_t) - (1/3)\ln(K_t) - (2/3)\ln(L_t)$.

[32] This is the context of poverty traps and equation (4) below. It can be shown that the large *h* coefficient here suggests that only the technology leader can avoid the poverty trap.

parameters in model (3). Condition (4) reflects the challenges of cathing up with the technology leader: the higher *g* or h^{max} the harder it is to catch up while the reverse holds when absorptive capacity, m, is large.

Benhabib and Spiegel (2005) used the Barro and Lee (2001) series EDU_BL as a measure of human capital. They estimated h^* to be 1.78 in 1960, and 1.95 in 1995. In 1960, there were 27 countries with EDU being below the threshold. By 1995, the number of nations at risk had declined to 4. We emulate their approach using the new index of human capital and the empirical estimates in column five in Table 3. Figure 3 summarises the results by human capital and distance to the frontier, D1970, in 1970 for three regional groups using h^* and the top 25% quartile of D1970 (i.e., nations closest to the frontier, that is the USA) as thresholds.

Using the new index of human capital, we find that there were 14 countries that were unable to meet condition (4) in 1970. Three decades later, that number had surged to 18 in 2000-03.[33] This finding contrasts with that of Benhabib and Spiegel (2005) reported above and calls for greater attention to skills that matter in development policy. Intuitively, the main drive of the increasing number of countries at risk is the very low level of *h* in the context of a relatively low diffusion effect (i.e., 0.048) – relatively to the local innovation effect (i.e., g =0.009=0.057-0.048) – which is not sufficient to offset the local innovation gains in advanced economies. The result is consistent with Hulten and Isaksson (2007) who find that the gap between rich and poor is likely to persist for some time.

The top panel of Figure 3 illustrates the fact that nations that failed to meet the 'catch-up condition' (top left) experienced minimal TFP productivity growth since 1975. On the other hand, countries that were far from the frontier and met condition (7) grow faster than others (see top centre). As a result, economies with very low levels of human capital stock in 1970 failed to catch-up; that is, they witnessed little change in terms of their level of backwardness in 2000-03 (bottom left). In fact, in this group, small improvements in human capital associate with divergence. In contrast, nations far from the frontier in 1970 seem to have improved their relative position substantially in 2000-03 as a result of investment in valuable skills (bottom centre). Developed nations closest to the frontier (bottom right) have benefited little from

[33] Note, h* was 3.5 in 1970 and 3.6 in 2000-03. There were five Asian nations in 'poverty trap' in 1970-74 but only India and Pakistan remained in the stagnant group in 2000-03. The number of African nations increased from nine to fifteen.

diffusion but are still leading (i.e., close to the frontier) as a result of the combination of a positive local innovation effect and a high valuable skills stock.

4. Sensitivity Analysis

In this section, we undertake sensitivity analysis to assess whether our system GMM results[34] are robust to two main assumptions. First, in factor analysis, we proposed that the new latent index was composed of four key indicators: TS_{t-2}, SciP, BKS, and T_ICT. We seek to examine how sensitive the estimates are to individual indicators. For instance, it may be argued that scientific books, BKS, may simply capture elite human capital effects more closely associated with R&D.[35] We utilised all book editions and not just scientific books and re-estimated model (3). Not reported here but available on request, we obtained system GMM estimates that are almost identical to those in column (3) in Table 3. Next, we examined the robustness of our results to the exclusion of T_ICT. We obtained 0.057 (0.018) and -0.040 (0.015) as estimates of h and $h\ln(A/A^{max})$ respectively. Although these estimates have the right sign, they imply that sixty-five of the seventy coutntries fall into a poverty trap. This suggests that trade in print media and ICT constitutes an important path to technology diffusion. Scientific research may also be seen as an elite form of human capital. Thus, we also examined the effect of excluding SciP in factor analysis. The coefficient estimate of h and $h\ln(A/A^{max})$ were 0.046 (0.01) and -0.048 (0.017) respectively. In discord with economic intuition, these imply that human capital does not contribute to domestic innovation and, as a result, all nations are capable of catching up with the leader. Although TS_{t-2} is critical for the identification of cognitive skills by the adult population, we also experimented with its exclusion. The estimates have the right sign but the local innovation effect, i.e., g in (3), implies that sixty-one nations experience stagnation which is implausible.

Finally, we sequentially replaced BKS and T_ICT with EDU_CS to investigate the impact of a direct quantitive measure of education. In both cases, we observed that neither h nor $h\ln(A/A^{max})$ have statistically significant coefficients. We interpret these

[34] Note that we also run cross-section regressions as in Benhabib and Spiegel (2005). We obtained the following coefficient estimates for h and $h\ln(A/A^{max})$ respectively: 0.036 (0.007) and -0.029 (0.006) for average 1970-2003 values of VS, standard errors in parentheses.

[35] We owe this conjecture to an anonymous referee.

results as support for the maintained view that valuable skills are more important than years of education.[36] Hence, the above suggest that the new latent factor and the empirical validity of the Benhabib and Spiegel (2005) model critically depend on all four indicators: cognitive skills of the adult population; scientific research; book production, and trade in print media and ICT.

Next, we investigate the sensitivity of our empirical results to alternative production functions given that the literature has seriously questioned the capacity of Cobb-Douglas production functions to illuminate on long-term growth patterns. This literature points to growing evidence in favour of production functions that account for capital-skill complementarities (CSC) and skill-biased-technical-change (SBTC).[37] Nelson and Phelps (1966) and Benhabib and Spiegel (1994, 2005) briefly discussed the former but never abandoned Cobb Douglas technology.

We seek to test the robustness of the logistic diffusion model (3) when we allow for CES and translog production technologies. This is particularly important in the light of Lopez-Pueyo, Barcenilla and Sanau (2008) who show that TFP growth and the identification of knowledge spillovers are sensitive to the form of production function assumed. Furthermore, we wish to examine whether the results in Table 3 stand when we account for CSC and SBTC, especially in view of the proposed idea of a direct link between valuable skills and human capital.

4.1 CES Production Technology: Calibration

First, we consider the CSC hypothesis. We adopt the two-level CES production function of Duffy, Papageorgiou and Perez-Sebastian (2004) but allow technology growth to be endogeneous, as proposed by Benhabib and Spiegel (2005). More formally, we define the log of TFP, $\ln A_t$, as follows:

$$\ln A_t = y_t - (1/\rho)\ln\left\{a\left[(bK_t^{\theta} + (1-b)S_t^{\theta}\right]^{\rho/\theta} + (1-a)N_t^{\rho}\right\} + e_t \qquad (5)$$

Here, y_t is again the log of per capital GDP, S_t is skilled labour, N_t is unskilled labour, θ is the Allen intra-class elasticity-of-substitution parameter between K and S,

[36] The robustness test results reported here carry through to analysis using CES and translog production functions below. These results are available on request.

[37] See papers by Krusell *et al.* (2000), Acemoglu and Zilibotti (2001), Duffy *et al*., (2004), Caselli (2005), Papageorgiou and Chmeralova (2005), and Kneller and Stevens (2006).

ρ is Allen inter-class elasticity-of-substitution between K and N. We calibrate (5) based on evidence in Krusell *et al.* (2000); i.e., we set a=1/3, b=0.5, θ=-0.4 and ρ=0.5.

Duffy *et al*. (2004) ponder about the definition of skilled labour, S, and experiment with various measures. Here, we define S=s*POP where s is VS re-scalled on the basis of the share of the population (POP) who have attained primary school, PRIM.[38] Table 4 displays the estimates that are very similar to those observed in Table 3, except that the coefficients of *h* now are higher in absolute value than those in when TIMSS and VS are considered. Thus, it seems that the innovation and diffusion effects of human capital observed in Cobb-Douglas technology are also present in CES production with capital-skill complementarity. Moreover, these strong results are intuitive and consistent with the idea that the capital-skill complementarity is best summarised by an index of human capital that more accurately reflects the actual level of cognitive skills employed at the time. Yet, we reserve judgment until we consider a translog production function that allows both CSC and SBTC.

4.2 **Translog Production Technology**: Calibration

The translog production function is a more flexible functional form that allows us to disentangle capital-skill complementary (CSC) effects from skill-biased-technical-change (SBTC) effects. We adapt the translog variable cost function of Papageorgiou and Chmeralova (2005) who take the physical capital stock to be a quasi-fixed factor but we also draw on Young (1992) and Mazumdar and Quispe-Agnoli (2004) to include technology in the cost function.

Following Young (1992) with constant returns to scale, ln*A* can be expressed as

$$\ln A = \ln Y - \left[\alpha \ln(K) + (1-\alpha)\left(\Theta_S \ln(S) + (1-\Theta_S)\ln(N) \right) \right] \qquad (6)$$

where lnA, K, S and N are as defined earlier and Θ_S is the share of skilled labour.

We construct a measure of lnA in the following steps: (a) we utilise estimates of (W_S/W_N) in Papageorgiou and Chmeralova (2005, column five, Table A.1); (b) we impute (W_S/W_N) for all countries,[39] and (c) calculate Θ_S as in Papageorgiou and

[38] We obtained similar but smaller coefficients when PRIM was used as a proxy of S.

[39] The imputed measure of (W_S/W_N) was on the basis of simultaneous quantile regressions of the Papageorgiou and Chmeralova (2005) estimates of (W_S/W_N) on urban density (URB),

Chmeralova (2005, p.64).[40] The latter facilitates a translog measure of ln*A* as in (6) and the estimation of model (3). Once again, we define skilled labour, S, as above: S=s*POP. We follow Papageorgiou and Chmeralova (2005) to involve ln(Y/L) as a regressor in order to account for a non-homothetic production function. Panel 1 in Table 5 summarises the GMM panel estimates of (3) that confirm the key role of valuable skills as an engine of technology growth. We again observe that the coefficient estimates for human capital and diffusion are positive and negative respectively, as expected. These estimates compare in absolute value to those in Table 3 rather than those in Table 4, except that the *h* coefficient is now smaller in most regressions. Overall, we conclude that the new latent index of 'valuable skills' plays a significant role in innovation and technology diffusion irrespective of the form of the production function assumed.

5. Conclusion

This paper develops a new index of human capital as a latent unobservable factor of cognitive skills that are employed by the adult population. It also examines the performance of this new index in a horse race against four alternative measures of human capital in the logistic model of technology diffusion proposed by Benhabib and Spiegel (2005). The robustness of the empirical results with respect to alternative assumption is tested by sensitivity analysis. This includes going beyond the Cobb-Douglas production function to consider alternative production functions that allow for capital-skill complementarity and skill-biased-technical-change in explaining trends in world growth.

Overall, the evidence shows that the new 'valuable skills' index best explains trends in technology growth since the 1970s. Moreover, it is the only measure of human capital that is consistent with the logistic model of diffusion. We conclude that valuable skills facilitate innovation and technology diffusion.

---

infant mortality (MoR), export manufactures (Xm), book publications (BKS), and a dummy variables for African nations (D_Africa).

[40] We apply the formula $\Theta_S = (W_S / W_N)S \big/ \left((W_S / W_N)S + N\right)$ where S=s*POP, s is VS re-scalled on the basis of the share of the population (POP) who have attained primary school. Again, we obtained similar results when PRIM was used as a proxy for S.

This new measure of human capital also reveals that long-term income disparities persist in countries that pay little attention to valuable skills. We find that the number of countries that are susceptible to poverty traps is much larger than previously thought. Many of these countries have remained stagnant and incapable of catching up over a thirty-year period. Although Africa and advanced OECD economies have invested heavily on education, they have witnessed a decline in valuable skills in recent times, in sharp contrast to Asian and South European nations who have invested heavily in employable skills. Finally, the new evidence calls for a re-think of education and development policy to pay more attention to the employability of cognitive skills by the working population.

Appendix: Variables Definitions and Sources.

Variable	Definitions and Sources
BKS	Imputed BOOKS where BOOKS stands for the log of the number of titles of non-periodical printed publications in the fields of pure and applied sciences per 100,000 people. Observations closest to the beginning of the period were used and 17 single period gaps were filled via linear interpolation. Summary of exp(BKS): Min= 0.1; Max=37, and Mean=7. *Source*: UNESCO Institute for Statistics.
$D_{i,t}$	Distance to the frontier in country i in period t, also expressed as (A/A^{max}). A is TFP and A^{max} is TFP in the leading country (USA) for the period.
EDU_BL	Average years of schooling of the total population aged 25 years and over. Since Barro and Lee (2001) data run up to 2000, we have calculated year 2000-2003 based on Kyriacou (1991) using gross school enrollment ratios of World Development Indicators. Maintaining Barro and Lee's (2001) 2000 figures, we spliced 2003 values to make them consistent and further adjusted for the 3 years difference. *Source*: Barro and Lee (2001), also BL (2001), and World Development Indicators (WDI).
EDU_CS	Revised estimates of average years of schooling of the total population aged 25 years and over by Cohen and Soto (2007). Given that these estimates are 10-year periods, we interpolated mid-decade estimates on the basis of the mid-point five-year distances in Barro and Lee (2001).
K	Net physical capital stock. We follow Benhabib and Spiegel (2005). Firstly, the initial value of capital stock is calculated as: $$\frac{K}{Y_{1960}} = \frac{I/Y}{\gamma + \delta + n}$$ where γ , δ and n represent output of growth rate per capita, depreciation rate of capital and average rate of growth of population respectively. Then the net capital stock for subsequent years is calculated as: $$K_t = K_0(1-\delta)^t + \sum_{i=1}^{t-1} I_i (1-\delta)^{t-i}$$ where I is investment (current prices) and δ is assumed to be 3%. The derived series of capital stock is then also compared with figures derived using Perpetual Inventory Method applied by PWT. *Source*: Penn World Tables (PWT 6.2).
L	Labour force (Employment). *Source*: PWT 6.2.
LPR	Log of labour force participation rate equal to (L/POP).
ly	Log of real per capita GDP (constant prices: Chain series) at the beginning of the period. *Source*: PWT 6.2.
MoR	Log of infant mortality rates. *Source*: UNCTAD Handbook of Statistics.
N	Unskilled labour set equal to (1-PRIM)*POP. *Source*: BL (2001) and PWT 6.2.
T_ICT	Log of the ratio of trade (i.e., sum of exports and imports) in print media and ICT equipment to real GDP ($US). We use the NBER-UN world trade dataset (see Feenstra *et al*. 2005, for details). Print media includes books, pamphlets, maps, newspapers, journals and periodicals. IT equipment consists of typesetting & founding machinery, printing machinery, bookbinding machinery, typewriters, word-processing machines, calculating machines, photocopying apparatus, office machines, data processing machines and equipment, and storage units for data processing. In terms of SITC Rev. 2 (4-digit) codes in Feenstra *et al*. (2005), we used classes 7263-7269; 7511-7529, and 8921-8922. Note, Botswana was merged with South Africa and 2000 figures and imports for India were missing. We re-distributed South Africa values on the basis of population and extrapolated the 2000 figures for India based on growth trends between 1997 and 1999. Summary of exp(T_ICT): Min= 0.00002; Max=0.29, and Mean=0.008.
POP	Population. *Source*: PWT 6.2.
PRIM	Log of Primary school attainment/100. *Source*: BL (2001).
S	Skilled labour set equal to PRIM*POP. *Sources*: BL (2001) and PWT 6.2.
SciP	Log of scientific journal article publications in sciences per 100,000 people. Summary of exp(SciP): Min= 0; Max=185, and Mean=22. *Source*: ISI Web of Knowledge.

SECO	Log of average years of secondary school attainment. *Source*: BL (2001).
TIMSS	Log of TIMSS (trends in international mathematics and science study): average Maths and Science scale scores of eighth grade students (Table C2) for the 2000-03 period. For 1970 to 1995, we use averages of mathematics and science for students aged 13-14 years in Barro and Lee (2001) for the periods 1970-72; 1982-84; 1988; 1990-91 and spliced at 1995. TIMSS data for pupils aged 13-14 years old in maths and/or science are available for 16 countries in 1970-72, 18 countries in 1982-84, 7 in 1988, 18 in 1990-91, and 37 in 1993-98. We use the mean of the two test scores and the latter estimates for the period 1995-99. Note, with the exception of South Africa, African economies are absent in TIMSS data. *Sources*: Barro and Lee (2001) and International Association for the Evaluation of Educational Achievement (IEA) 1995, 1999, and 2003.
URB	Log of per capita urban labour force at the initial year of the period. *Source*: WDI.
WAR	Years of armed interstate and intrastate conflict in which there were more than 1,000 casualties, excluding the top 25 OECD countries. *Source*: Uppsala Conflict Data Program (UCDP) at the Department of Peace and Conflict Research, Uppsala University and Centre for the Study of Civil War at the International Peace Research Institute, Oslo (PRIO). Version 4-2008.
X*m*	Log of per capita manufacturers exports. *Source*: WDI.

6.

7. References

Abowd, J. M., Haltiwanger, J., Jarmin, R., Lane, J., Lengermann, P., McCue, K., McKinney, K., Sandusky, K. (2005), The relation among human capital, productivity and market value: Building up from micro evidence, in Corrado, C., Haltiwanger, J. C. and Sichel, D. E. (eds.), *Measuring capital in the new economy*, 153-204, Studies in income and wealth, *65*, Cambridge: National Bureau of Economic Research (NBER).

Acemoglu, D., Aghion, P., Zilibotti, F. (2002), Distance to frontier, selection, and economic growth, NBER Working Paper No. 9066, Cambridge: NBER.

Acharya, R. C. and Keller, W. (2007), Technology transfer through imports, NBER Working Paper No. 13086, Cambridge: NBER.

Aghion, P. and Howitt, P. (1998) *Endogenous growth theory*, Cambridge, MA: MIT Press.

Alders, P. (2005), Human capital growth and destruction: The effect of fertility on skill obsolescence, *Economic Modelling, 22*(3), 503-520.

Apergis, N., Economidou, C. and Fillipidis, I. (2009), Innovation, technology transfer and labor productivity linkages: Evidence from a panel of manufacturing industries, *Review of World Economics*, 144(3), 491-508.

Arellano, M. and Bover, O. (1995), Another look at the instrumental variable estimation of Error-Components Models, *Journal of Econometrics, 68*(1), 29-52.

Aristotle (1976), Nicomachean Ethics, Revised Edition, Tranlation by J. Thomson, London: Penguin.

Baten, J. and van Zanden, J. (2008), Book production and the onset of modern economic growth, *Journal of Economic Growth*, *13*(3), 217-35.

Barro, R. J. (2002), Education as a determinant of economic growth, in Lazear, E. P. (ed.), Education in the twenty-first century, 9-24, Stanford: Hoover Institution Press.

Barro, R. and Lee, J. (2001), International data on educational attainment: Updates and Implications, *Oxford Economic Papers*, *53*(3), 541-563.

Becker, G.S. (1964) *Human capital: A theoretical and empirical analysis with special reference to education*, New York, NBER.

Benhabib, J. and Spiegel, M. (1994), The role of human capital in economic development: Evidence from aggregate cross-country data, *Journal of Monetary Economics*, *34*(2), 143-174.

Benhabib, J. and Spiegel, M. (2005), Human capital and technology diffusion, in Aghion, P. and Durlauf, S. N. (eds.), *Handbook of economic growth*, *1A*, 935-966, Handbooks in economics, *22*, Amsterdam and San Diego: Elsevier, North-Holland.

Bils, M. and Klenow, P. J., (2000), Does schooling cause growth?, *American Economic Review*, *90* (5), 1160-83.

Borghans, L. and Heijke, H. (2005), The production and use of human capital: Introduction, *Education Economics*, *13*(2), 133–142.

Bourdieu, P. (1977) *Outline of a theory of practice*, Cambridge University Press.

Brogan, R. D. and Erickson, E. W. (1975), Capital-skill complementarity and labor earnings, *Southern Economic Journal*, *42*(1), 83-88.

Caselli, F. (2005), Accounting for cross-country income differences, in Aghion, P. and Durlauf, S. N. (eds.), *Handbook of economic growth*, *1A*, 679-741, Handbooks in economics, *22*, Amsterdam and San Diego: Elsevier, North-Holland.

Cheng, M. Y. and Ghulam, R. (2007), Knowledge gap and earnings differential in the knowledge-based economy, *Applied Economics Letters*, *14*(3), 219-222.

Ciccone, A. and Papaioannou, E. (2005), Human capital, the structure of production, and growth, European Central Bank, Working Paper Series: 623.

Coe, D. T. and Helpman, E. (1995), International R&D spillovers, *European Economic Review*, *39*(5), 859-887.

Cohen, D. and Soto, M. (2007), Growth and human capital: Good data, good results, *Journal of Economic Grow*th, *12*(1), 51-76.

Coulombe, S., Tremblay, J. and Marchand, S. (2004), Literacy scores, human capital and growth in fourteen OECD countries, Human Resources and Skills Development Canada, Statistics Canada, Minister of Industry, Catalogue No. 89-552-MIE.

Dagum, C. and Slottje, D. J. (2000), A new method to estimate the level and distribution of household human capital with application, *Structural Change and Economic Dynamics*, *11* (1-2), 67-94.

Destre, G., Levy-Garboua, L. and Sollogoub, M. (2008), Learning from experience or learning from others? Inferring informal training from a human capital earnings function with matched employer-employee data, *The Journal of Socio-Economics*, *37* (3), 919-38.

DeLong, J. B. and Summers, L. H. (1991), 'Equipment Investment and Economic Growth', *Quarterly Journal of Economics 106*(2), 445-502.

Dewey, J. (1916) *Democracy and education: An introduction to the philosophy of education*, New York: Macmillan.

Dowrick, S. (2003), Ideas and education: level or growth effects?, NBER Working Paper No. 9709, Cambridge: NBER.

Dowrick, S. and Rogers, M. (2002), Classical and technological convergence: beyond the Solow-Swan growth model, *Oxford Economic Papers*, *54* (3), 369-385.

Duane, F. Alwin (2007) *Margins of Error: A Study of Reliability in Survey Measurement*, Hoboken, NJ: John Wiley & Sons.

Duffy, J., Papageorgiou, C. and Perez-Sebastian, F. (2004), Capital-skill complementarity? Evidence from a panel of countries, *Review of Economic and Statistics*, *86* (1), 327-344.

Durlauf, S. N., Johnson, P. A. and Temple, J. R. W. (2005), Growth econometrics, in Aghion, P. and Durlauf, S. N. (eds.), *Handbook of economic growth*, *1A*, 555-677, Handbooks in economics, *22*, Amsterdam and San Diego: Elsevier, North-Holland.

Easterly, W. and Levine, R. (2001), It's not factor accumulation: Stylized facts and growth models, *The World Bank Economic Review 15* (2), 177-219.

Ehrlich, I. (2007), The mystery of human capital as engine of growth, or why the US became the economic superpower in the 20th century, NBER Working Paper 12868, Cambridge: NBER.

Falvey, R., Foster, N. and Greenaway, D. (2007), Relative backwardness, absorptive capacity and knowledge spillovers, *Economics Letters*, *97*, 230–234.

Feather, J. (2003) *Communicating Knowledge: Publishing in the 21st Century*, Munich: K.G. Saur.

Feenstra, R.C., Lipsey, R.E., Deng, H., Ma, A.C and Mo, H. (2005), World trade flows: 1962-2000, NBER Working Paper No. 11040, Cambridge: NBER.

Flossmann, A. L., Piatek, P. and Wichert, L. (2006), Going beyond returns to education: The role of noncognitive skills on wages in Germany, Working Paper, University of Konstanz, ZEW, September.

Fortson, J. (2008), Mortality risk and human capital investment: The Impact of HIV/AIDS in Sub-Saharan Africa, American Economic Association Annual Meeting, January 2008.

Gallup, J. L., Sachs, J. and Mellinger, A. D. (1999), Geography and economic Development, *International Regional Science Review*, *22*(2), 179-232.

Galor, O. (2005), From stagnation to growth: Unified growth theory, , in Aghion, P. and Durlauf, S. N. (eds.), *Handbook of economic growth*, *1A*, 935-966, Handbooks in economics, *22*, Amsterdam and San Diego: Elsevier, North-Holland.

Galor, O. and Weil, D.N. (2000), Population, technology and growth: From Malthusian stagnation to the demographic transition and beyond, *The American Economic Review*, 90 (4), 806-828.

Gault, F. (2005) Measuring knowledge and its economic effects: The role of official statistics, Advancing Knowledge and the Knowledge Economy Conference, National Academies of Science, Washington D. C.

Gorlich, D. and de Grip, A. (2007) Human capital depreciation during family-related career interruptions in male and female occupations, Kiel Institute for the World Economy, Working Paper No. 1379.

Griliches, Z. (1981), Market value, R&D, and patents, *Economic Letters*, 7, 183-187.

Hanushek, E. A. and Kimko, D. D. (2000), Schooling, labor-force quality, and the growth of nations, *American Economic Review*, *90* (5), 1184-1208.

Hanushek, E. and Wößmann, L. (2007) The role of school improvement in economic development, NBER Working Paper No. 12832, Cambridge: NBER.

Hartog, J. and Oosterbeek, H. (2007), What should you know about the private returns to education?, in Hartog, J. and van den Brink, H. M. (eds.), *Human capital: theory and evidence*, 7-10, New York: Cambridge University Press.

Heckman, J., Stixrud, J. and Urzua, S. (2006), The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior, *Journal of Labor Economics*, *24* (3), 411-482.

Hulten, C. R. and Isaksson, A. (2007) Why development levels differ: The sources of differential economic growth in a panel of high and low income countries, NBER Working Paper No. 13469, Cambridge: NBER.

Ingold, T. (2000), Evolving skills, in Rose, H. and Rose, S. (eds.), *Alas, poor Darwin: Arguments against evolutionary psychology*, 225-246, London: Jonathan Cape.

Jamison, E.A, Jamison, D.T. and Hanushek, E. (2007), The effects of education quality on income growth and mortality decline, *Journal of Economic Growth*, 26 (6), 772-789.

Jones, G. (2008) Cognitive ability and technology diffusion: An empirical test, American Economic Association Annual Meeting, January 2008.

Jones, G. and Schneider, W. J. (2006), Intelligence, human capital, and economic growth: A Bayesian averaging of classical Estimates (BACE) Approach, *Journal of Economic Growth*, *11* (1), 71-93.

Joss, R. L. (2001), Management, *Australian Journal of Management*, *26* (Special Issue), 89-103.

Kneller, R., and Stevens, P.A. (2006), Frontier technology and absorptive capacity: Evidence from OECD manufacturing industries. *Oxford Bulletin of Economics and Statistics 68* (1), 1-21.

Korpi, T. and Tahlin, M. (2007) Educational mismatch, wages and wage growth: Overeducation in Sweden, 1974-2000, Swedish Institute for Social Research (SOFI), Stockholm University, Working Paper No. 10/2007.

Krueger, A. and Lindahl M. (2001), Education for growth: Why and for whom?, *Journal of Economic Literature*, *39* (4), 1101-1136.

Krusell, P., Ohanian, L.E., Rìos-Rull, J. and Violante, G.L. (2000), Capital-skill complementarity and inequality: A macroeconomic analysis, *Econometrica*, *68* (5), 1029-1053.

Kyriacou, G. (1991) Level and growth effects of human capital, working paper 91-26, CV Starr Centre, New York: NY.

Lane, P.W. (2002), Generalized linear models in soil science, *European Journal of Soil Science*, *53*(2), 241-251.

Lanzi, D. (2007), Capabilities, human capital and education, *The Journal of Socio-Economics*, *36*(3), 424-435.

Le, T., Gibson, J. and Oxley, L. (2003), Cost and income-based measures of human capital, *Journal of Economic Surveys*, *17* (3), 271-307.

Lévy-Garboua, L., Damoiselet, N., Lassibille, G. and Navarro-Gomez, L. (2004), An economist's view of schooling systems, in Sofer, C. (ed.), *Human capital over the life cycle*, 53-68, London: Edward Elgar.

Lopez-Pueyo, C., Barcenilla, S. and Sanau, J. (2008), International R&D spillovers and manufacturing productivity: A panel data analysis, *Structural Change and Economic Dynamics*, *19*(2), 152-172.

Lucas, Robert E. Jr., (1988), On the Mechanics of Economic Development, *Journal of Monetary Economics*, *22*(1), 3-42.

Lynn, R. and Vanhanen, T. (2002) *IQ and the Wealth of Nations*, Westport, CT: Praeger Publishers.

Madsen, J. (2007), Technology spillover through trade and TFP convergence: 135 years of evidence for the OECD countries, *Journal of International Economics*, *72*(2), 464-480.

Mazumdar, J. and Quispe-Agnoli, M. (2004) Can capital-skill complementarity explain the rising skill premium in developing countries? Evidence from Peru, Working Paper 2004-11, Federal Reserve Bank of Atlanta.

Messinis, G. and Ahmed, A. (2009) Human capital, innovation and technology diffusion, Centre for Strategic Economic Studies, Victoria University, Working Paper No 43.

Nelson, R. and Phelps, E. (1966), Investment in humans, technology diffusion, and economic growth, *American Economic Review*, Papers and Proceedings, *56* (2), 69-75.

Nelson, R. (2005) *Technology, institutions and economic growth*, Cambridge, Mass.: Harvard University Press.

Nordman, C. J. and Wolff, F. (2007) On-the-job learning and earnings in Benin, Morocco and Senegal, Institut de Recherche Pour le Developpement, Working Paper DT/2007-09.

Papageorgiou, C. and Chmeralova, V. (2005), Nonlinearities in capital-skill complementarity, *Journal of Economic Growth*, *10* (1), 59-89.

Paxson, C. and Schady, N. (2007), Cognitive development among young children in Ecuador: The roles of wealth, health, and parenting, *Journal of Human Resources*, *42*(1), 49-84.

Pfeiffer, F. and Reuß, K. (2007) Age-dependent skill formation and returns to education, ZEW Discussion Paper No. 07-015, Zentrum für Europäische Wirtschaftsforschung, Mannheim.

Pritchett, P. (2001), Where has all the education gone?, *World Bank Economic Review*, *15*(3), 367-391.

Psacharopoulos, G. and Patrinos, H. A. (2004), Returns to investment in education: A further update, *Education Economics*, *12*(2), 111-134.

Robst, J. (2007), Education, college major, and job match: Gender differences in reasons for mismatch, *Education Economics*, *15* (2), 159-175.

Rogers, E. M. (2005) *Diffusion of innovations*, 5th Edition, New York: Free Press.

Romer, P. M. (1990), Endogenous technological change, part II, *The Journal of Political Economy*, *98*(5), 71-102.

Schultz, T. P. (1999), Health and schooling investments in Africa, *Journal of Economic Perspectives*, *13*(3), 67-88.

Schultz, T. W. (1961), Investment in human capital, *American Economic Review*, *51*(1), 1-17.

Schumpeter, J. (1934) *The theory of economic development. An inquiry into profits, capital, credit, interest, and the business cycle*. Cambridge: Harvard University Press.

Sen, A. (1997), Human capital and human capability, *World Development*, *25* (12), 1959-1961.

Temple, J. (1999), The new growth evidence, *Journal of Economic Literature*, *37* (1), 112-156.

Tsoukalas, C. (1976), Some aspects of over-education in modern Greece, in Dimen, M. and Friedl, E. (eds.), *Regional variation in modern Greece and Cyprus: Toward a perspective on the ethnography of Greece*, 419-428, New York Academy of Sciences.

Vandenbussche, J., Aghion, P. and Meghir, C. (2006), Growth, distance to frontier and composition of human capital, *Journal of Economic Growth*, *11*(2), 97-127.

Windmeijer, F., (2005), A finite sample correction for the variance of linear efficient two-step GMM estimators, *Journal of Econometrics 126*(1), 25-51.

Wößmann, L. (2003), Specifying human capital, *Journal of Economic Surveys*, 17(3), 239-70.

Wolff, E. N. (2001), The role of education in the postwar productivity convergence among OECD countries, *Industrial and Corporate Change*, *10* (3), 735-59.

Young, A. (1992), A Tale of Two Cities: Factor Accumulation and Technical Change in Hong Kong and Singapore. In NBER, *Macroeconomics Annual 1992*. Cambridge, MA: MIT

Figure 1. Valuable Skills Growth, 1970-2003: Best and Worst Performers

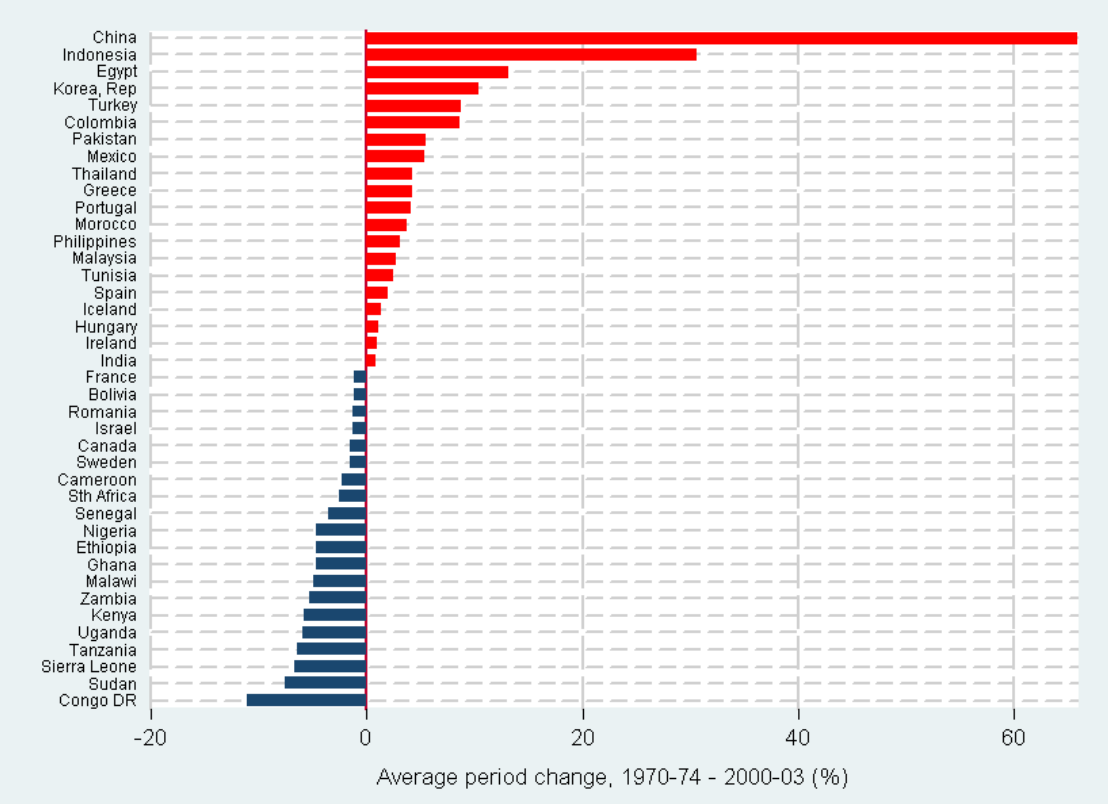


Figure 2. Formal Education and Valuable Skills: 1970-2003

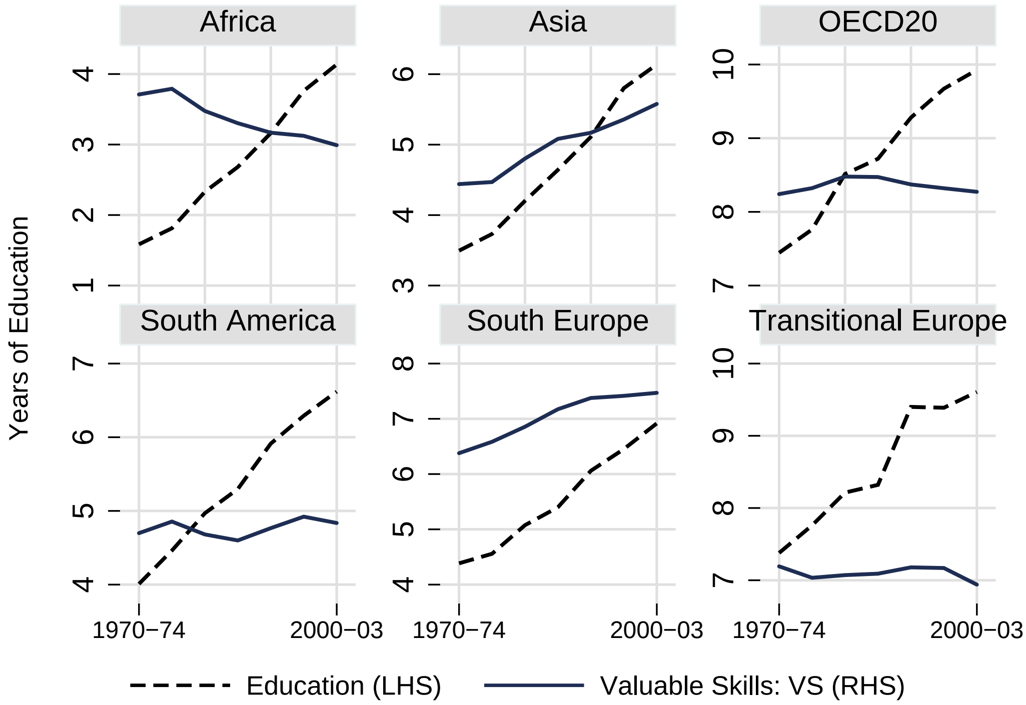
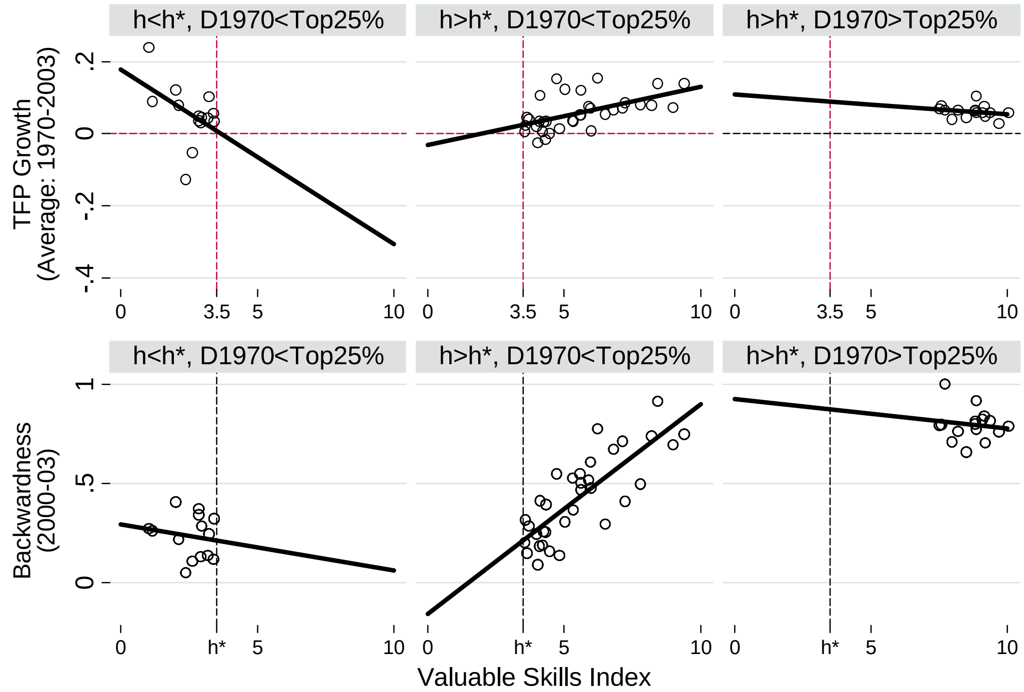


Figure 3. Valuable Skills, Diffusion and Poverty Traps: 1970-2003



Notes: The USA was the technology leader. D1970 is 'Distance to the Frontier' in 1970. There were 14 and 18 nations with h below h* values of 3.5 and 3.6 in 1970-74 and 2000-03 respectively. For details, see Table 2

Table 1. Modelling TIMSS and Books in Sciences: Panel Estimation

Variables	$E_t[TIMSS_t \mid I_t]$	$E_{t+2}[TIMSS_t \mid I_{t+2}]$	$E_t[BOOKS_t]$
	(1)	(2)	(3)
Constant	7.537 (0.188)**	8.268 (0.346)**	3.134 (0.379)**
SECO	0.120 (0.026)**	0.116 (0.068)	
HIGH	0.142 (0.023)**	0.297 (0.079)**	
EDU_BL	-0.072 (0.010)**	-0.083 (0.025)**	
MoR	-0.161 (0.021)**	-0.402 (0.054)**	-0.393 (0.094)**
LPR	0.521 (0.169)**	1.235 (0.268)**	0.909 (0.240)**
SciP			0.299 (0.039)**
WAR			-0.136 (0.024)**
D_miss	-0.153 (0.029)**	-0.343 (0.072)**	
D_East_Euro	0.211 (0.034)**	0.468 (0.072)**	
D_Africa			-1.255 (0.143)***
Observations	122	52	296
LR χ^2	400.22**	13978.04**	1762.10*

Note: Standard-errors in parentheses and *,** denote 5% and 1% level of significance. SECO, HIGH and EDU_BL are secondary education attainment, tertiary education participation rate and years of education from Barro and Lee (2001), MoR is infant mortality rate, LPR is labour participation rate, and SciP is per capita scientific publications; all six are in logs. WAR is the number of years in internal and external armed conflict if casualties exceeded 1,000 battle-related deaths in non-OECD countries. D_miss, D_East_Euro, D_Africa are indicator variables for missing observations in at least 4/5 periods (80%); East Europe transitional economies, and Africa respectively. In column (2), all explanatory variables are forwarded two periods.

Table 2. New Estimates of Human Capital: Valuable Skills

Country	1970-74	1975-79	1980-84	1985-89	1990-94	1995-99	2000-03
Algeria	**2.855**	3.089	2.628	2.748	2.557	2.790	**2.835**
Argentina	6.007	5.705	5.824	5.617	5.504	5.563	5.523
Australia	8.823	8.863	8.943	8.780	8.491	8.332	8.211
Austria	7.502	7.688	8.027	8.133	7.800	7.765	7.820
Belgium	8.178	8.264	8.320	8.274	8.125	8.106	8.064
Bolivia	3.983	4.261	3.871	3.990	3.938	4.032	3.645
Botswana		5.404	5.392	4.774	4.366	4.391	4.751
Brazil	5.333	5.384	5.260	5.062	4.980	5.285	5.372
Cameroon	**2.970**	3.372	3.189	3.183	2.879	2.769	**2.496**
Canada	9.356	9.239	9.179	8.964	8.762	8.515	8.356
Chile	5.903	6.256	5.804	5.717	6.059	6.177	6.135
China	**1.028**	2.346	3.794	4.729	4.963	5.415	5.770
Colombia	**2.839**	4.248	3.761	3.645	4.034	4.401	4.549
Congo DR	**2.380**	2.217	1.494	1.911	1.596	0.920	**0.538**
Denmark	9.081	9.145	9.308	9.100	8.869	8.626	8.594
Egypt	**2.016**	4.534	4.753	3.999	3.824	3.934	3.871
Ethiopia	**3.166**	2.429	2.251	2.480	2.648	2.625	**2.129**
Finland	9.002	9.234	9.015	9.148	9.142	9.147	8.890
France	8.860	8.703	8.553	8.548	8.512	8.235	8.121
Germany	8.198	8.261	8.312	8.424	8.230	8.109	8.108
Ghana	4.109	4.235	3.449	3.400	3.024	3.006	**2.755**
Greece	5.570	5.789	6.416	6.850	7.042	7.079	7.192
Hungary	7.811	7.830	7.739	7.832	7.668	8.245	8.395
Iceland	7.578	7.902	8.123	8.206	8.182	8.349	8.314
India	**3.212**	3.468	3.555	3.628	3.277	3.482	**3.397**
Indonesia	**1.163**	0.866	1.814	2.146	2.342	2.694	3.650
Ireland	8.444	8.867	9.387	9.190	9.003	9.064	9.010
Israel	9.188	9.413	9.164	8.791	8.357	8.301	8.320
Italy	7.138	7.317	7.426	7.535	7.362	7.288	7.245
Japan	8.484	8.561	8.795	8.769	8.655	8.594	8.539
Kenya	4.815	4.495	3.954	3.970	3.520	3.269	**2.866**
Korea, Rep	4.721	4.958	6.062	6.968	7.181	7.620	8.148
Malawi	**3.390**	3.256	1.792	2.323	2.319	2.781	**2.229**
Malaysia	5.612	5.763	5.732	5.722	6.157	6.591	6.675
Mauritius	6.237	6.457	5.097	5.457	5.753	5.863	5.735
Mexico	4.343	4.125	4.646	4.844	5.247	5.671	5.973
Morocco	3.707	3.936	3.707	3.933	4.243	4.551	4.683
Netherlands	8.820	8.959	9.064	9.089	9.085	9.119	9.071
New Zealand	7.986	8.043	8.143	7.928	7.705	7.577	7.501
Nigeria	4.479	4.975	4.751	4.204	3.590	3.153	**3.021**
Norway	8.861	8.987	8.998	8.872	8.708	8.556	8.387
Pakistan	**2.122**	2.124	3.078	3.168	2.828	2.594	**2.943**
Paraguay	3.585	3.714	3.832	3.912	4.312	4.337	**3.450**
Peru	4.320	3.729	3.690	3.647	3.631	3.797	4.114
Philippines	4.243	4.204	4.175	4.274	4.667	4.997	5.158
Poland	7.248	7.278	7.531	7.494	7.296	7.412	7.337
Portugal	5.985	6.060	6.224	6.782	7.244	7.412	7.676
Romania	6.520	5.995	5.945	5.947	5.657	5.852	5.942
Senegal	4.215	4.630	3.898	2.444	3.318	3.497	**3.171**
Sierra Leone	**2.603**	2.258	2.349	1.976	1.833	1.263	**1.377**
Singapore	9.390	9.298	8.558	9.265	9.855	9.892	9.709
Sth Africa	5.321	5.453	5.452	5.134	4.518	4.516	4.349
Spain	6.820	7.172	7.360	7.529	7.860	7.885	7.768
Sri Lanka		3.318	4.178	3.958	3.448	3.501	3.714
Sudan	**2.907**	3.101	2.576	2.316	1.985	1.692	**1.354**
Sweden	10.031	10.025	10.043	9.837	9.439	9.192	8.955
Switzerland	9.695	9.705	9.692	9.561	9.300	9.116	9.013
Tanzania	3.626	3.525	2.394	2.407	2.549	2.276	**1.994**
Thailand	5.039	5.018	4.835	5.591	6.073	6.294	6.531
Tunisia	4.127	4.702	3.853	4.441	4.581	4.701	4.831
Turkey	**3.405**	3.340	3.939	4.631	4.889	5.169	5.488
Uganda	3.561	2.992	1.863	1.847	1.702	1.897	**2.084**
U.K.	9.147	9.117	9.097	8.966	8.807	8.652	8.496
U.S.A.	7.716	7.795	7.880	7.862	8.206	8.068	7.874
Uruguay	5.619	5.548	5.404	5.207	5.672	5.788	5.905
Zambia	4.019	3.761	3.588	3.356	2.909	2.850	**2.538**
Zimbabwe		0.791	4.572	3.064	2.819	2.856	**3.206**

Note : Estimates of the new index of human capital or 'valuable skills' are equivalent years of education. In bold are human capital levels below the poverty threshold levels where the latter was equal to 3.5 and 3.6 equivalent years of education in 1970-74 and 2000-03 respectively.

Table 3. Logistic Technology Diffusion (Benhabib and Spiegel 2005): Alternative Human Capital Measures

Explanatory Variables	Education		Cognitive skills		Valuable skills
	EDU_BL	EDU_CS	TIMSS (original)	TS_{t-2} (imputed)	VS
	(1)	(2)	(3)	(4)	(5)
Constant	0.073	0.019	-1.150**	-0.035	-0.123
	(0.046)	(0.035)	(0.386)	(0.047)	(0.083)
h	-0.009	0.001	0.167**	0.012	0.057**
	(0.010)	(0.010)	(0.047)	(0.011)	(0.016)
$h(A_i/A^{max})$	0.010	0.005	-0.023*	-0.001	-0.048**
	(0.008)	(0.010)	(0.009)	(0.008)	(0.015)
Observations	409	362	106	405	405
AB AR(1)	2.65**	2.59**	0.81	2.99	3.82**
AB AR(2)	1.24	0.43	0.02	0.68	0.80
Hansen: χ^2	40.39*	29.61	5.97	37.63	29.90

Note: Standard-errors in parentheses and *,** denote 5% and 1% level of significance. Following Krueger and Lindahl (2001), *h* stands for years of education. EDU_BL and EDU_CS are the Barro and Leee (2001) and Cohen and Soto (2007) estimates of years of education respectively, TS_{t-2} is imputed TIMSS. VS is the new latent index of 'valuable skills'. We used lags 2-3 of *h* and $h(A_i/A^{max})$ as instrumental variables, except in (3) where only the second lag is used due to limited observations. Available on request are estimates of time effects and Hansen tests of exogeneity of instruments; none of the latter reject the null hypothesis of exogeneity.

Table 4. CES Technology in Benhabib and Spiegel (2005) model: Alternative Human Capital Measures

Explanatory Variables	Education		Cognitive skills		Valuable skills
	EDU_BL	EDU_CS	TIMSS (original)	TS_{t-2} (imputed)	VS
	(1)	(2)	(3)	(4)	(5)
Constant	0.131*	0.126*	-1.712**	0.080	-0.105
	(0.057)	(0.058)	(0.419)	(0.068)	(0.055)
h	0.003	-0.0002	0.257**	0.009	0.069**
	(0.013)	(0.013)	(0.050)	(0.014)	(0.017)
$h(A_i/A^{max})$	0.003	0.008	-0.032**	0.004	-0.045**
	(0.012)	(0.012)	(0.008)	(0.009)	(0.015)
Observations	399	359	100	399	399
AB AR(1)	3.76**	3.47**	2.14*	3.62**	4.15**
AB AR(2)	1.87	1.45	1.24	1.51	1.61
Hansen: χ^2	35.38	32.87	4.86	33.42	31.02

Note**:** See Table 3 for definitions and notation.

Table 5. Translog Production Technology and Logistic Diffusion: Alternative Human Capital Measures

	Education		Cognitive skills		Valuable skills
Explanatory Variables	EDU_BL	EDU_CS	TIMSS (original)	TS_{t-2} (imputed)	VS
	(1)	(2)	(3)	(4)	(5)
Constant	-0.001	0.015	-1.148**	-0.054	-0.118
	(0.049)	(0.041)	(0.404)	(0.067)	(0.061)
h	0.005	-0.001	0.169**	0.016	0.045**
	(0.013)	(0.012)	(0.047)	(0.015)	(0.016)
$h(A_i/A^{max})$	0.001	0.008	-0.030**	-0.008	-0.033*
	(0.012)	(0.012)	(0.011)	(0.012)	(0.013)
Observations	397	357	100	397	397
AB AR(1)	2.67**	2.39**	2.15*	2.79**	2.99**
AB AR(2)	0.64	0.51	0.32	0.12	0.20
Hansen: χ^2	34.46	29.92	6.68	40.53*	28.95

Note**:** See Table 3 for definitions and notation.