

Cognitive Skills, Innovation and Technology Diffusion

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

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Victoria University
Melbourne

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

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George Messinis[†] and Abdullahi D. Ahmed

Centre for Strategic Economic Studies,
Victoria University
Australia

Abstract

This paper examines the Benhabib and Spiegel (2005) model of technology diffusion using a new latent index of human capital and competing indicators that include the Barro and Lee (2010) estimates. The new index is a measure of education quality for seventy nations in 1970-2003. Analysis utilises both cross-section and dynamic panel GMM estimation and extends beyond the Cobb-Douglas production technology. The new evidence indicates that (i) the new index is most consistent with the model; (ii) the skills-education gap has widened in Africa and advanced OECD countries, and (iii) capital-skill complementarities and skill-biased-technical-change have become global phenomena.

Keywords: Education; Skills; Human capital; Growth; Innovation; Diffusion; CSC; SBTC

JEL Classification: I2, O1, O3, O4

[†] 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

Human capital¹ is considered to be the engine of economic growth² and there exist several models that seek to explain this. 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. 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 accumulation of human capital is highlighted by the former school while it is the stock of human capital that is important in the latter; what Dowrick (2003) calls *growth effects* and *level effects* respectively.

Assimilationist theories have 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 endogenous growth highlighting the role of innovation and sustainable growth (Romer 1990; Aghion and Howitt 1998).³

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, Foster, and Greenaway 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.⁴ The idea originates in Nelson and Phelps (1966) who assessed education to be a catalyst in the diffusion of

¹ Although human capital has been defined as the ‘knowledge, skills, competencies and other attributes’ that are relevant to economic activity (OECD, 1998), the empirical growth literature has overwhelmingly utilised educational attainment as a proxy.

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

³ There are also attempts to reconcile these two traditions in a unified growth theory. Examples are Aghion, Howitt and Murtin (2010), Galor and Weil (2000) and Galor (2005).

⁴ 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).

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.⁵

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, the Solow ‘residual’ or total factor productivity (hereafter TFP) 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.⁶ 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 model⁷ 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.

⁵ This has been empirically confirmed by Vandenbussche, Aghion and Meghir (2006).

⁶ As summarised in Temple (1999) and Easterly and Levine (2001).

⁷ An alternative account of economic stagnation is Acemoglu, Aghion and Zilibotti (2002).

The principal objective of this paper is to re-examine the Benhabib and Spiegel (2005) model of logistic diffusion with two key innovations. First, the paper utilises a new measure of human capital that focuses on the complementarity between skills acquired through schooling and IT equipment related facilitating the application of cognitive skills. In brief, the new human capital index is a composite latent index of three key indicators: the share of the adult population who have completed secondary education; per capita scientific research output in science, and per capita trade in IT educational equipment. This rests on the idea that technological growth requires both cognitive skills *and* their application at the workplace. IT educational equipment reveals the degree to which cognitive skills are employed by the adult population.

Second, we account for model uncertainty by considering alternative forms of production technology,⁸ alternative estimates of human capital, and alternative estimation techniques. Thus, in testing the Benhabib and Spiegel (2005) hypothesis, we run the new index in a horse race against competing measures of human capital. Also, we relax the assumption of a Cobb-Douglas production function to consider two alternative forms: the constant-elasticity of substitution (CES) function of Duffy, Papageorgiou, and Perez-Sebastian (2004), and the translog production function of Papageorgiou and Chmeralova (2005). These extensions are motivated by mounting evidence in favour of capital-skill complementarities (CSC) and skill-biased-technical-change (SBTC). Finally, the paper employs both dynamic panel data and cross-sectional data econometrics to gain insights on the dynamic relation between human capital and growth, and to address concerns associated with measurement errors.⁹

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 and tests its reliability. Section four reports the estimation results in testing the logistic diffusion model of Benhabib and Spiegel (2005). Section five conducts sensitivity analysis and section six and concludes.

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.

⁹ For a review of growth econometrics issues, see Durlauf, Johnson and Temple (2005).

2. Knowledge Diffusion: Three Models

In general, theories of human capital and growth define output, Y , to be of the general functional form: $Y_{j,t} = F(A_{j,t}(H_{j,t}), X_{1j,t}, \dots, X_{nj,t})$ 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, \dots, 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:

$$Y_t = A_0 K_t^\alpha L_t^\beta \varepsilon_t \quad (1)$$

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 endogenous 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:

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

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 (i.e., absorptive capacity) 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).

Benhabib and Spiegel (1994) take the log difference of (1) and substitute for (2) to arrive at the growth equation:

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.

$$\Delta y_t = c + \alpha \Delta k_t + \beta \Delta l_t + (g - m)h_t + mh_t(A_t^{\max} / A_t) + u_t \quad (3)$$

where y_t , k_t and l_t are Y_t , K_t and L_t in logs respectively. Equation (3) predicts that, in addition to growth in physical capital and labour, Δk and Δl , economic growth will also depend on the stock of human capital and the distance to the frontier; u_t is a serially correlated error term. 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 $(g-m)/m$.

In a second model, Dowrick and Rogers (2002) propose a model that is different to Benhabib and Spiegel (1994) in three ways. First, it accounts for growth effects by allowing human capital to enter as a direct factor of production. Second, although it maintains Nelson and Phelps' (1966) original idea of diffusion, it does not admit a human capital effect in local innovation. Third, it controls for neoclassical convergence; that is, initial per worker output, Y_0 , enters as an independent factor. More formally, their empirical specification is of the type:

$$\Delta y_t = \beta \ln(Y_0) + mh_t \ln(A_t^{\max} / A_t) + \alpha \Delta k_t + \gamma \Delta h_t + u_t \quad (4)$$

Dowrick and Rogers (2002) define Δy_t as the growth rate of real GDP per worker. The first two terms in (4) represent a hybrid model of technological catch-up: neoclassical convergence to the steady state of y , and technology diffusion. Note the fourth term allows for growth effects as in Lucas (1988).

A third model is that of logistic diffusion as proposed by Benhabib and Spiegel (2005). They modify (2) to 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 frontier¹¹

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

due to technology clusters or an incompatibility with domestic technology or social values (Rogers, 2005). More formally, logistic diffusion takes the following form¹²:

$$\Delta a_t = gh_t + mh_t \left[\frac{A_t^{\max} - A_t}{A_t} \right] \left[\frac{A_t}{A_t^{\max}} \right] = (g + m)h_t - mh_t \left[\frac{A_t}{A_t^{\max}} \right] + e_t \quad (5)$$

Compared to the exponential model in (2), diffusion in (5) is moderated by the inverse of the distance to the frontier, also known as ‘backwardness’, (A/A^{\max}). As a 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. A New Index of Human Capital

3.1 Background

Due to data limitations, existing international studies on the role of human capital in technology diffusion have overwhelmingly adopted educational attainment as a proxy for human capital.¹³

Benhabib and Spiegel (2005, 1994) and Dowrick and Rogers (2002) abstract from measurement issues and utilise educational attainment measures of human capital.¹⁴ However, these measures are highly problematic in international studies for several reasons.¹⁵ 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.¹⁶ Last but not least

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 $s=1$. On the basis of the evidence in Benhabib and Spiegel (2005), this study considers only these two scenarios.

¹³ It is only recently that alternative, broader definitions have surfaced in the empirical literature. Hanushek and Wößmann (2009; 2007) and Jones (2008) emphasise cognitive skills while Aghion, Howitt and Murtin (2010) highlight the role of health.

¹⁴ Note, existing *panel* studies employ data that pre-dates 1990 and so do other diffusion models such as Acemoglu, Aghion and Zilibotti (2006). The study by Aghion, Howitt and Murtin (2010) is an exception, though it does not employ educational attainment as a measure of human capital and only OECD countries are considered in system GMM estimation.

¹⁵ 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.

¹⁶ These problems have been well documented in Bils and Klenow (2000), Wößmann (2003), Le, Gibson, and Oxley (2003), Abowd *et al.* (2005), and Joss (2001).

important, they often evolve in correlation with other macroeconomic variables that introduces endogeneity biases in estimation.

More recently, the literature has searched for qualitative measures of human capital. One possibility is the relaxation of the Nelson and Phelps (1966) assumption that all education is useful for technology diffusion. Thus, Acemoglu, Aghion and Zilibotti (2006), Ciccone and Papaioannou (2005), and Vandenbussche, Aghion, and Meghir (2006) decompose education and suggest that primary or secondary education is more suitable for adoption while higher education is best for innovation.¹⁷ Although higher education can intuitively contribute to economic innovation (Romer 2000), the variable is also susceptible to reverse causality (Bils and Klenow 2000) and appropriate instruments are hard to find at the national level (Vandenbussche, Aghion, and Meghir 2005; Aghion *et al.* 2009).

An alternative account 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 This is the general methodology employed here at the macro-level to account for the quality of education (i.e., cognitive skills).

The potential discrepancy between education and skills has been emphasised in various forms. 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 literature of job training (Borghans and Heijke, 2005; Nordman and Wolff, 2007; Destre, Levy-Garboua, and Sollogoub, 2008; Robst, 2007).

¹⁷ Hanushek and Wößmann (2007) and the skill decomposition approaches are two interpretations of why education failed to stimulate growth in less developed countries (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 Folloni and Vittadini (2010) for a comprehensive survey of alternative methodologies in the measurement of human capital.

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, Tremblay, and Marchand (2004) and Hanushek and Wößmann (2009, 2007) confirm a link between test scores and economic performance¹⁹. The latter study suggests that the skills-education deficit is greater in developing countries²⁰ 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).²¹

3.2 A New Human Capital Index

In this section, we consider human capital as a composite index that jointly accounts for the following key dimensions of human capital: cognitive skills acquired at school, cognitive skills used in scientific research, and the employment of modern educational IT equipment as complementary to cognitive skills. Hence, the new index seeks to measure cognitive skills as currently employed by the adult population.²²

In an exhaustive literature survey on the history of human capital measurement, Folloni and Vittadini (2010) strongly recommend the search for human capital as a latent variable. They maintain that the approach is in the spirit of Schultz' (1961) emphasis on 'knowledge and skills that have economic value'. The emphasis on value is in the light of (a) time-varying returns to education (Psacharopoulos and Patrinos, 2004; Hartog and Oosterbeek, 2007); (b) the importance of skill obsolescence (Alders, 2005; Gorlich and de Grip, 2007; Pfeiffer and Reuß, 2007), and (d) evidence of skill-job mismatch and overeducation (Cheng and Ghulam, 2007; Korpi and

¹⁹ In contrast, Jones and Schneider (2006) and Jones (2008) utilise the cross-section international IQ test scores published by Lynn and Vanhanen (2002).

²⁰ 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.

²¹ 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'.

²² 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.

Tahlin, 2007). Further, several studies have also proposed the latent factor approach as a strategy in dealing with measurement errors and endogeneity.²³

We exploit new data not available to Hanushek and Kimko (2000) and Dagum and Slottje (2000) in order to estimate a new index of human capital as an unobservable latent factor that measures the level of skills acquired in secondary education that are employed by the adult population; we maintain that this composite index measures the level of cognitive skills employed by the adult population. Hanushek and Kimko (2000) utilise international test scores in maths and science (TIMSS) to impute cross-section measures of cognitive skills from regressions, assuming that quality of schooling evolves slowly over time. Dagum and Slottje (2000) estimate human capital as a latent variable using household survey data. However, none of these indicators are direct measures of intelligence or education quality (Le, Gibson, and Oxley 2003).

We utilise a multiple-indicator model with one latent common factor:

$$I_{k,jt} = \mu_k + \lambda_k h_{jt}^S + e_{k,jt} \quad (6)$$

$I_{k,jt}$ is the log of indicator $k=1,\dots,n$ of country j at time t , h_{jt}^S is the common factor, λ_k is the factor loading, and e_k is an idiosyncratic error term. The common factor is the unobserved characteristic of cognitive 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 three series, in logs: the share of the adult population who completed secondary education, SECO, per capital scientific publications in science, SciP, and per capita trade in research IT equipment, RITE.²⁴ The use of secondary education as a key indicator is suggested by Rogers (2008) and is highly relevant in this study where the emphasis is on research skills. Persons who have completed secondary education are expected to have acquired basic research skills that are critical for frontier research as well as understanding new technology. It also seems intuitive that the SciP bibliometrics measure would reflect the quality of human research capital. Gault (2005) argues that the process of knowledge creation - closely interlinked with technological progress - by academic scientist can be measured by academic publications. Finally, RITE is to

²³ See, for instance, Temple (1999), Durlauf, Johnson and Temple (2005), and Heckman, Stixrud, and S. Urzua (2006).

²⁴ For detailed sources and definitions of all variables, see the Appendix. A complete data set of the indicator series and new estimates in this study are also available by the authors.

acknowledge the importance of information technology as key in the application of cognitive skills and research. The focus on educational IT also rests on economic intuition of a link between trade and skilled human capital (Galor and Weil, 2000) and the importance of trade as a means to technology transfer (Apergis, Economidou, and Fillipidis, 2009; Madsen, 2007). Here, however, we focus on trade of IT equipment that directly relates to cognitive skills, research capacity and, thus, the quality of education.

SECO and SciP contain information on cognitive skills while RITE contributes information on the level of applied research skills. The existence of a single principal factor common to all three indicators is likely to measure cognitive skills that have economic value. We acknowledge that the single index approach adopted here may be limiting if the role of human capital in innovation and diffusion can only be captured by multiple measures of human capital. Also, 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, both of these claims are still an empirical question. We maintain that the selected indicators are essential components of the human capital index targeted here.

These three indicators (i.e., SECO, SciP, and RITE) enter in iterated principal-component factor analysis. Table 1 presents the factor score estimates for the three indicators. Not reported here are eigenvalues and model selection information criteria (AIC and BIC) that clearly indicate the existence of a single factor. The estimated factor scores suggest that per capital trade in IT research equipment, RITE, is the most important indicator of the three with a weighting of 0.61 in the early 1970s that rises to 0.74 in the late 1980s and back to 0.66 in the most recent period. Scientific publications contribute about 20% to the principal factor but secondary education seems to play a very small part towards cognitive skills. Not reported due to space limitations, factor loading estimates suggest that secondary education and scientific research are important ingredients in the formation of human capital. Moreover, the results suggest that it is cognitive skills that associate with IT equipment that is the most important component of human capital.

- Table 1 about here -

The new human capital index, henceforth denoted as SKILLS²⁵, may be measured with error. In reliability tests, we compare the new index to the following alternatives: average years of education by Barro and Lee (2010), EDU; average years of education of Cohen and Soto (2007), EDU_CS; and TIMSS tests scores.²⁶ Assume h_1 and h_2 are two alternative estimates of the true series, h^* . Following Krueger and Lindahl (2001), the reliability ratio of series h_1 with respect to h_2 is $R(h_1, h_2) = \text{cov}(h_1, h_2) / \text{var}(h_1)$. If the measurement errors of h_1 and h_2 are uncorrelated, the probability limit of $R(h_1, h_2)$ is $\text{var}(h^*) / [\text{var}(h_1) + \text{var}(e_1)]$ where e_1 is the measurement error of h_1 . Thus, the reliability ratio represents the fraction of the variance of h_1 that is due to the true variance of h^* . Given that $R(h_1, h_2)$ is the coefficient estimate of h_1 in a bivariate regression with h_2 as the explained variable, Table 2 presents reliability ratios for the four measures in levels, and conditional on the log of per capital real GDP in 1970-73. These are bivariate bootstrap quantile regression coefficient estimates.²⁷ When compared to EDU, the reliability ratio of SKILLS in levels is 1.03 while that of EDU is 0.73. The new index also seems to perform better against EDU_CS and TIMSS. Table 2 shows that SKILLS also outperforms all three alternatives in conditional regressions.²⁸ Overall, we conclude that the new latent index of ‘cognitive skills’ performs better than existing measures.

- Table 2 about here -

Figure 1 compares the performance of individual countries over time in terms of months of education, EDU, and cognitive skills, SKILLS. It measures the average annual change over the period of 1975-2003. Clearly, some countries that experienced growth in educational attainment were amongst the bottom 20 in terms of employable cognitive skills, SKILLS. Sweden, Nigeria, Sudan, Congo Democratic Republic and Paraguay were amongst the worst performers. In contrast, applied cognitive skills surged in China, the Republic of Korea, Thailand, Zimbabwe and Indonesia. For example, the SKILLS index in Indonesia has recorded an annual average increase of

²⁵ Data, programs and panel estimates of the SKILLS index are available on request.

²⁶ The Appendix has more details. Note, for comparability, EDU_CS, TIMSS and SKILLS were rescaled into equivalent years of education, EDU, using robust panel FGLS, for Lane (2002) shows that GLS estimation minimises the bias in random variable transformations.

²⁷ Similar results were obtained when robust regressions were employed.

²⁸ We also considered SECO and the cross-section IQ series of Lynn and Vanhanen (2002). The new SKILLS index was still observed to be superior.

(education equivalent) one month. Most striking is China with a record change of 2.1 months increase although it has recorded only an annual 1.6 months rise in years of education, EDU.

- Figure 1 about here -

Figure 2 illustrates the education-skill gap for six regional groups: advanced OECD20 countries, South America, Asia (excluding Japan and South Korea), Africa, transitional economies in Europe and South Europe.²⁹ The results confirm the Hanushek and Wößmann (2007) finding of a ‘skills deficit’ in developing economies; i.e., developed countries are further behind on measures of cognitive skills than they are with respect to average years of formal education, EDU, that has surged in most regions. Further, the new SKILLS index suggests that the stock of employable cognitive skills has been on a secular downward trend since 1970-74 in Africa, it has improved through to 1980s but fell in the 1990s in South Europe, and it has been volatile without any long-term trend in East Europe and in South America. More surprising, the index has declined sharply in OECD20 countries since the 1980s. In addition, Asia has witnessed the greatest gains in cognitive skills over the whole period, although it remains behind the levels recorded in Europe and OECD countries.

- Figure 2 about here -

4. Panel and Cross-section Estimation Results

This section re-examines the logistic diffusion model of Benhabib and Spiegel (2005) in (5) using three alternative measures of human capital are utilised to test. In order to account for heterogeneity and the potential for endogeneity, we employ the *System GMM* panel estimator of Arellano and Bover (1995).³⁰ Although lagged variables are not a full proof strategy against endogeneity, lags 2-4 are used to

²⁹ 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.

³⁰ The ‘xtabond2’ STATA 10 procedure of Roodman (2009b) was employed in a two-step robust estimation that accounts for fixed and time effects, and finite-sample correction on the basis of Windmeijer (2005).

instrument human capital stock, h , and technology diffusion, $h(A/A^{\max})$. The ceiling on the number of instruments is intended to limit the problem of proliferation of instruments that can overfit endogenous variables (Roodman 2009a).

We utilise the new latent index of cognitive skills, SKILLS, in system GMM regressions to estimate the three models of technology diffusion outlined above. For comparison, we express the Benhabib and Spiegel (1994) and Dowrick and Rogers (2002) models in terms of Δa as the dependent variable. It can be shown that the results clearly point to the logistic model of diffusion as the model most consistent with the data.³¹

Below, we focus on the main objective of this paper which is to re-examine the Benhabib and Spiegel (2005) model of logistic technology diffusion utilising three alternative measures of human capital: the average years of education series of Barro and Lee (2010), EDU; the original TIMSS series (TIMSS), and the new latent index of cognitive skills, SKILLS.³²

Columns 1-3 in Table 3 present system panel GMM estimates of the Benhabib and Spiegel (2005) model. Note that the data reveal that USA is the technology leader.³³ Regression (1) utilises years of education, EDU, regression (2) uses TIMSS test scores, and regression (3) utilises the new cognitive skills measure, SKILLS. The results indicate that only when the SKILLS series is used as a measure of human capital we obtain statistically significant coefficients that have the expected sign. The coefficient estimates in column (3) suggest that SKILLS contribute to both domestic innovation and technology diffusion. The net effect of human capital on total factor productivity growth depends on how far from the frontier a country is. For the leader, the net productivity growth effect of one (education equivalent) year of cognitive skills is 0.008 (=0.062-0.054), the domestic innovation effect. For the median country, the net effect would be 0.035 (=0.062 - 0.5*0.054).

Table 3 also reports the number of instruments used, the number of panel units, the Arellano-Bover AR(1) and AR(2) tests for autocorrelation, and the Hansen test of over-identifying restrictions. While the AR(1) is expected to be significant at 5%

³¹ Details are available upon request.

³² An earlier draft also used the Cohen and Soto (2007) estimates of years of education and the log of secondary education attainment, SECO, from Barro and Lee (2010) in all regressions. The results were similar to those reported for EDU here. Estimates are available on request.

³³ 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., $\ln(A_t) = \ln(Y_t) - (1/3)\ln(K_t) - (2/3)\ln(L_t)$.

level, AR(2) is a specification test. In all regressions the AR(2) and Hansen statistics are not significant, the latter confirming the validity of the instruments used.

- Table 3 about here -

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 world. That capacity, they argue, depends on a critical threshold level of human capital. Nations with human capital levels below that threshold stagnate and can remain behind for decades. They derive this threshold or ‘catch-up condition’ to be:

$$h_t^* = \exp\left(\frac{sg \ln(h_t^{\max})}{sg + m}\right) \quad (7)$$

In the case of logistic diffusion, $s=1$, h_t^{\max} is human capital in the leading country in period t (see footnote 12), and g and m are parameter estimates of the human capital stock and diffusion parameters in model (5). Condition (7) reflects the challenges of catching up with the technology leader: the higher g or h^{\max} the harder it is to catch up while the reverse holds when m is large.

Benhabib and Spiegel (2005) used the Barro and Lee (2001) estimates of average years of education as a proxy for 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 regression (3) in Table 3. Figure 3 summarises the results by human capital and distance to the frontier in 1970, $D1970$, for three sub-groups using h^* and the top 25% quartile of $D1970$ (i.e., the frontier, that happens to be the USA) as thresholds.

Using the new index of human capital, we find that there were 13 countries that were unable to meet condition (7) in 1970. Three decades later, that number had risen to 15 in 2000-03.³⁴ This finding contrasts with that of Benhabib and Spiegel (2005)

³⁴ Note, h^* was 3.2 in 1970-74 and 3.1 in 2000-03. There were four Asia nations in ‘poverty trap’ group in 1970-74: China, Indonesia, India and Pakistan – only the latter two remained in that group in 2000-03. There were nine Africa countries in 1970-74: Congo DR, Egypt, Ethiopia, Nigeria, Sierra Leone, Sudan, Tanzania, Uganda and Zimbabwe. In 2000-03, Egypt and Zimbabwe had left the stagnation group.

reported above and calls for greater attention to skills that matter in development policy. Intuitively, the main cause of the inability of countries at risk to catch up with the rest of the world is the low level of h in the context of a relatively low diffusion effect (i.e., 0.054) – as compared to the local innovation effect of 0.008 – 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.

- Figure 2 about here –

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 1970-74. On the other hand, countries that were far from the frontier and met condition (7) grew faster than others (see top centre). As a result, economies with very low levels of human capital stock in 1970-74 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 1970-74 seem to have improved their relative position substantially in 2000-03 as a result of investment in cognitive skills (bottom centre). Developed nations closest to the frontier (bottom right) have benefited little from 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 cognitive skills stock.

So far, empirical work has explored panel data in an attempt to expand the sample size and control for reverse causality. However, panel data estimators can magnify measurement errors (Hauk and Wacziarg, 2009; Durlauf, Johnson and Temple, 2005). Thus, we next turn to cross-country regressions using total sample period averages of the key variables. Regressions (4)-(6) in Table 3 present the estimation results which suggest that only the TIMSS coefficient estimate of h in regression (5) is statistically significant and with the expected sign. However, the estimate is implausibly large when compared to that of $h(A/A^{\max})$,³⁵ although the limited observations in regression (5) make comparisons difficult.

³⁵ This is the context of poverty traps and equation (7) above. It can be shown that the large h coefficient here suggests that only the technology leader can avoid the poverty trap.

The evidence presented here highlights the importance of a latent approach to measuring human capital, as advocated by Folloni and Vittadini (2010). Moreover, the new evidence calls for a policy shift towards cognitive skills, especially skills that complement new technology. The case in favour of cognitive skills is strengthened by the fact that only the cognitive skills measures, i.e., TIMSS and SKILLS, are most consistent with the Benhabib and Spiegel (2005) model.³⁶

The results reported here are also important for they provide both dynamic panel and cross-section evidence of the important contribution human capital makes in local innovation and in technology diffusion. Using cross-section data, Hanusheck and Wößmann (2009, 2007) have already shown that there is a causal relationship between the cognitive skills of young students (i.e., TIMSS test scores) and economic growth in the world. The evidence here supports the view that cognitive skills can also explain growth in technology and technology diffusion. The latter is particularly crucial for it provides hope that less developed nations can benefit from new technology. However, the empirical evidence clearly shows that schooling is not enough. What is required is a mix of schooling, research capacity and IT tools that can employ cognitive skills towards the expansion of human capital.

5. Sensitivity Analysis

In this section, we examine the sensitivity of system GMM and cross-section OLS regression results to the number of lagged instruments and to alternative production technologies. First, we examine the robustness of the estimation results to a reduced number of lagged instruments. Roodman (2009a) showed that results can be highly sensitive to the number of instruments used and emphasised the importance of this. Thus, we reduced the number of instruments to 2-3 lags for each explanatory variable. It can be shown that both system GMM and cross-section OLS regression results are almost identical to those reported in Table 3.³⁷

Further, we tested the sensitivity of the empirical results to alternative production functions given that the growing evidence in favour of production functions that

³⁶ Of course, this is not *ipso facto* evidence that the cognitive skills measures are absolutely superior to the Barro and Lee (2010) measures of educational attainment. The latter may very well be important in different analyses or different growth models, as seems the case with the model considered by Barro and Lee (2010).

³⁷ This also applies to the results reported in Tables 4-5 below.

account for capital-skill complementarities (CSC) and skill-biased-technical-change (SBTC).³⁸ 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, equation (5), 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 cognitive skills and human capital.

5.1 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 endogenous, as proposed by Benhabib and Spiegel (2005). More formally, we define the log of TFP, $\ln A_t$, as follows:

$$\ln A_t = y_t - (1/\rho) \ln \left\{ a \left[(bK_t^\theta + (1-b)S_t^\theta)^{\rho/\theta} + (1-a)N_t^\rho \right] \right\} + e_t \quad (8)$$

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, ρ is Allen inter-class elasticity-of-substitution between K and N. We calibrate (8) based on evidence in Krusell *et al.* (2000); i.e., we set $a=1/3$, $b=0.5$, $\theta=-0.4$ and $\rho=0.5$.

Duffy, Papageorgiou, and Perez-Sebastian (2004) ponder about the definition of skilled labour, S, and experiment with various measures. Here, we define $S=s*POP$ where s is equal to the share of the adult population who has completed secondary education and POP stands for population.³⁹ Columns (1)-(3) in Table 4 display the system GMM estimates that are very similar to those observed in Table 3. Again, with

³⁸ See papers by Krusell *et al.* (2000), Duffy, Papageorgiou, and Perez-Sebastian (2004), Caselli (2005), Papageorgiou and Chmeralova (2005), and Kneller and Stevens (2006).

³⁹ Again, similar coefficients estimates were obtained when primary education attainment was used as a proxy for s.

the exception of EDU, the coefficient estimates have the right sign but are statistically significant only when the new human capital index, SKILLS, is employed. Also, the size of the estimates and the gap between domestic innovation and technology diffusion human capital effects are lower higher in absolute value than those in Table 3 when SKILLS is considered. Thus, it appears that human capital defined as a latent index of cognitive skills also contributes to innovation and diffusion under CES production with capital-skill complementary.

In contrast, the cross-section OLS regression coefficients estimates are not statistically significant. These cross-section results cast doubt on the validity of the model or the form of the production technology. Thus, we reserve judgment until we consider a translog production function that allows both the CSC and SBTC hypotheses to be nested.

- Table 4 about here -

5.2 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 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 translog variable cost function:

$$\begin{aligned} \ln C = & \alpha_0 + \alpha_Y \ln Y + \sum_i \alpha_i \ln W_i + \alpha_K \ln K + \alpha_A \ln A + \alpha_{YK} \ln Y \ln K + \\ & \frac{1}{2} \left(\alpha_{YY} (\ln Y)^2 + \sum_i \sum_j \alpha_{ij} \ln W_i \ln W_j + \alpha_{KK} (\ln K)^2 + \alpha_{AA} (\ln A)^2 \right) + \\ & \frac{1}{2} \left(\sum_i \sum_j \rho_{ij} \ln W_i \ln K_j + \alpha_{AA} (\ln A)^2 + \sum_j \rho_{Yi} \ln Y \ln W_i \right) + \alpha_{AK} \ln A \ln K \end{aligned} \quad (9)$$

W_i is the price of variable production input i (where $i = S, N$), K is physical capital, and A_i is technology. Using Shepard's lemma, we obtain an expression for the share of skilled labour in the variable cost function as:

$$\Theta_S = \frac{\partial \ln C}{\partial \ln P_S} = \alpha_S + \alpha_Y \ln Y + \sum_j \gamma_{Sj} \ln W_j + \alpha_K \ln K + \alpha_A \ln A \quad (10)$$

Assuming homogeneity of degree one in variable input prices (i.e., $\gamma_S + \gamma_N = 0$) we have

$$\Theta_S = \alpha_S + \gamma_K \ln(K / Y) + \gamma_S \ln(W_S / W_N) + \gamma_Y \ln(Y / L) + \gamma_A \ln A \quad (11)$$

Model (11) says that the share of skilled labour in the wage fund, Θ_S , is a function of the capital-output ratio, (K/Y), the relative price of skilled labour, (W_S/W_N), real output per worker, (Y/L), and technology, A; all in logs. It nests the following hypotheses: (a) complementarity (substitutability) between K and S: $\gamma_K > 0$ ($\gamma_K < 0$); (b) complementarity (substitutability) between S and N: $\gamma_S > 0$ ($\gamma_S < 0$); (c) homothetic production: $\gamma_Y = 0$; and (d) skill-biased technical change (SBTC) in favour (at the expense) of skilled labour: $\gamma_A > 0$ ($\gamma_A < 0$).

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

$$\ln A = \ln Y - \left[\alpha \ln(K) + (1 - \alpha) (\Theta_S \ln(S) + (1 - \Theta_S) \ln(N)) \right] \quad (12)$$

We construct a measure of $\ln A$ 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,⁴⁰ and (c) calculate Θ_S as in Papageorgiou and Chmeralova (2005, p.64).⁴¹ The latter facilitates a translog measure of $\ln A$ as in (12) and the estimation of models (5) and (11). 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. Columns (1)-(3) in Table 5 summarise the system GMM coefficient estimates. Again, the evidence is similar to that reported above where the SKILLS index is most consistent

⁴⁰ 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 secondary education (SECO), and dummy variables for Sub-Saharan Africa, Eastern European transitional economies and South American nations.

⁴¹ We apply the formula $\Theta_S = (W_S / W_N) S / ((W_S / W_N) S + N)$ where $S = s * POP$, s is the share of the population who has completed secondary education (Barro and Lee, 2010) while POP is total population. Again, we obtained similar results when the primary education equivalent series was used as a proxy for s.

with the model, except that now the null hypothesis of technology diffusion is rejected only at 10% significance level.

Furthermore, the cross-section OLS regression estimates in columns (4)-(6) are now statistically significant for SKILLS and its coefficients seem to be of plausible value and with the right signs. Again, the local innovation coefficient for TIMSS is again extremely large when compared to the $h(A_i/A^{\max})$ coefficient, as in Tables 3-4. Overall, the magnitude of the coefficient estimates in Table 5 compare to those in Table 3 rather than those in Table 4.⁴² The evidence indicates that the new latent index of cognitive skills plays a significant role in innovation and technology diffusion. However, only under a translog production technology the cross-section evidence is consistent with the system GMM findings.

- Table 5 about here -

Finally, we utilise the new estimates of Θ_S , (K/Y) and (W_S/W_N) to test the validity of model (11), and the results appear in Table 6. In order to compare our results with Papageorgiou and Chmeralova (2005), we employ simultaneous quantile regressions (i.e., simultaneous estimation of the lowest and highest quartiles) to account for nonlinearities and report results for the early 1980s, 1990s and 2000s. The results indicate that the CSC hypothesis, once a unique feature of developed economies, has become a global phenomenon since the early 1990s. Further, we find limited evidence of skilled-unskilled labour complementarity. Further, the SBTC effect seems to have increased since the 1990s. Finally, our findings suggest that the production function is non-homothetic, as in Papageorgiou and Chmeralova (2005).

- Table 6 about here -

⁴² We also experimented with the replacement of secondary education, SECO, with years of education, EDU, in both factor analysis and in the estimation of equation (5). We obtained similar system GMM estimates but the cross-section OLS coefficient estimates were no longer significant in the Cobb-Douglas and CES specifications. Yet, the cross-section estimates for SKILLS were highly significant statistically under translog production technology.

Hence, the evidence in this section provides support for the CSC and SBTC hypotheses and suggests that these effects, once exclusively developed-world effects, have become global phenomena.⁴³

6. 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 two 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 reducing the set of instrument variables in system GMM estimation and going beyond the Cobb-Douglas production function to consider CES and translog production functions.

Overall, the evidence shows that the new cognitive skills index outperforms existing measures of human capital. Moreover, it is the only measure that is consistent with the logistic model of diffusion in dynamic panel data analysis. Thus, we conclude that cognitive skills facilitate innovation and technology diffusion.

This new measure of human capital also reveals that long-term income disparities persist in countries that pay little attention to cognitive 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 cognitive skills in recent times, in sharp contrast to Asian and South European nations who have invested heavily in skills. The new evidence calls for a re-think of development policy to pay more attention to the cognitive skills of the working population.

Finally, it would be insightful to extend the analysis in future research to other growth models and test their performance using the new index of human capital. For, example, it would be important to examine whether the new index of cognitive skills proposed here can bridge the gap between assimilation and accumulation theories. Put

⁴³ We also experimented with an alternative series of skilled labour, S , where the latent index of skills was normalised to be in the range $[0, 1]$. The estimates were very similar to those in the Tables 4-7 and are available from the authors.

differently, will the new human capital index assist towards a unified theory whereby the quality of education remains the key driver of world economic growth?

Appendix: Variables Definitions and Sources.

Variable	Definitions and Sources
D_{i,t}	Distance to the frontier in country <i>i</i> in period <i>t</i> , also expressed as (A/A^{\max}) . <i>A</i> is TFP and A^{\max} is TFP in the leading country (USA) for the period.
EDU	Average years of schooling of the total population aged 25 years and over. Estimates for Ethiopia and Nigeria are based on Cohen and Soto (2007). <i>Source</i> : Barro and Lee (2010), http://www.barrolee.com , and Cohen and Soto (2007).
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, mid-decade estimates were linearly interpolated.
IQ	IQ scores. <i>Source</i> : Lynn and Vanhanen (2002)
K	Net physical capital stock. Following Benhabib and Spiegel (2005), the initial 1960 value of capital stock, K_{1960} , is calculated as: $\frac{K_{1960}}{Y_{1960}} = \frac{I/Y}{\gamma + \delta + n}$ where <i>I</i> , γ , δ and <i>n</i> represent real investment (constant prices), growth in real GDP per capita, depreciation rate of capital (fixed at 3%), and the rate of population growth respectively. The net capital stock for subsequent years is calculated as: $K_t = K_{1960}(1 - \delta)^t + \sum_{i=1}^{t-1} I_i(1 - \delta)^{t-i}$ <i>Source</i> : Penn World Tables (PWT 6.2).
POP	Population. <i>Source</i> : PWT 6.2.
RITE	The log of per million of people trade (i.e., sum of exports and imports) in IT equipment (\$US) relating to research activity. We use the NBER-UN world trade dataset. IT equipment consists of 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 <i>et al.</i> (2005), we used classes 7511-7529. Note, Botswana was merged with South Africa and 2000 imports estimates for India were missing. South Africa estimates (merged with Botswana) were re-distributed on the basis of manufactured trade as a share of merchandise trade. The 2000 figures for India were extrapolated on the basis of growth trends between 1997 and 1999. Eighty per cent of estimates for the former USSR were attributed to Russia and the 1991-92 trade shares were extrapolated backwards for the former Czechoslovakia and distributed to Slovakia appropriately. <i>Source</i> : Feenstra <i>et al.</i> (2005) and WDI.
S	Skilled labour set equal to $\exp(\text{SECO}) * \text{POP} / 100$. <i>Sources</i> : Barro and Lee (2010), Cohen and Soto (2007) and PWT 6.2.
SciP	The log of scientific journal article publications in sciences per million of people. We added 0.1 to original data. <i>Source</i> : ISI Web of Knowledge.
SECO	The log of the percentage of the total population aged 25 years and over who completed secondary education. We added 0.01 to original data and estimates for Ethiopia and Nigeria are based on Cohen and Soto (2007). <i>Source</i> : Barro and Lee (2010) and Cohen and Soto (2007).
TIMSS	The 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. <i>Sources:</i> Barro and Lee (2001) and International Association for the Evaluation of Educational Achievement (IEA) 1995, 1999, and 2003.
Y	Real GDP (constant prices: Chain series). <i>Source:</i> PWT 6.2.

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Table 1. Human Capital as a Latent Factor: Factor Scores

	Indicators			Observations
	SECO	SciP	RITE	
1970-1974	0.15	0.25	0.61	70
1975-1979	0.15	0.23	0.62	70
1980-1984	0.11	0.20	0.69	70
1985-1989	0.08	0.19	0.74	70
1990-1994	0.09	0.20	0.71	70
1995-1999	0.11	0.21	0.67	70
2000-2003	0.12	0.22	0.66	70

Note: SECO, SciP and RITE stand for the share of population aged 25 and over who completed secondary education, per capita scientific publications in sciences, and per capita trade in research IT equipment respectively. All three are in logs. Estimates of principal factor were obtained by iteration and but principal component analysis also produced similar results. The factor scores were produced by the Bartlett method and are normalised to sum to unity.

Table 2. Alternative Measures of Human Capital: Reliability Tests

SKILLS	EDU	EDU_CS	TIMSS	Sample size
Levels: Bivariate Bootstrap Quantile Regressions (median)				
1.03**	(0.07)	0.73**	(0.08)	70
1.05**	(0.07)	0.72**	(0.08)	61
1.66**	(0.27)		0.31** (0.07)	53

Conditional Levels: Bivariate Bootstrap Quantile Regressions (median)				
0.64**	(0.21)	0.30*	(0.11)	67
0.57**	(0.27)	0.33	(0.11)	60
1.11**	(0.34)		0.28** (0.07)	50

Note: Standard-errors in parentheses and *,** denote 5% and 1% level of significance respectively. SKILL is the new latent index from factor analysis, EDU is years of education estimates by Barro and Lee (2010), EDU_CS is the Cohen and Soto (2007) estimates of years of education, and TIMSS is the TIMSS test scores. For more details, see the Appendix. Bootstrapping in quantile regressions used 1000 replications in STATA 10. Also, jackknife robust regressions produced similar estimates.

Table 3. Logistic Technology Diffusion (Benhabib and Spiegel 2005)

Variables	System GMM (panel)			OLS Regression (cross-section)		
	EDU	TIMSS	SKILLS	EDU	TIMSS	SKILLS
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.086	-0.731	-0.122	0.031	-0.134	-0.018
	(0.055)	(0.511)	(0.082)	(0.023)	(0.090)	(0.038)
h	-0.016	0.110	0.062**	0.005	0.056*	0.020
	(0.011)	(0.066)	(0.023)	(0.006)	(0.027)	(0.010)
$h(A_i/A^{\max})$	0.023*	-0.018	-0.054**	-0.002	-0.023	-0.014
	(0.010)	(0.014)	(0.020)	(0.006)	(0.015)	(0.008)
Sample size	409	106	409	70	53	70
Instruments	40	27	40			
Countries	70	46	70			
AR(1)	-3.96**	0.57	4.05**			
AR(2)	-1.42	-1.12	1.57			
Hansen: χ^2	41.04	10.88	40.17			

Note: Standard-errors in parentheses and *,** denote 5% and 1% level of significance. EDU is years of education estimates by Barro and Lee (2010), TIMSS is the TIMSS test scores, and SKILLS is the new latent index of education quality or cognitive skills. Following Krueger and Lindahl (2001), h stands for years of education and is equivalent to $\ln(H)$; In all regressions, we limited the number of instrument to lags 2-4 of h and $h(A_i/A^{\max})$ in order to avoid the problem of proliferation of instruments that can overfit endogenous variables (Roodman 2009a). AR(1) and AR(2) are Arellano-Bover tests for autocorrelation. Available on request are estimates of time effects.

Table 4. CES Technology in Benhabib and Spiegel (2005) model

Variables	System GMM (panel)			OLS Regression (cross-section)		
	EDU (1)	TIMSS (2)	SKILLS (3)	EDU (4)	TIMSS (5)	SKILLS (6)
Constant	0.049 (0.064)	-1.830 (1.221)	-0.141 (0.092)	0.017 (0.030)	-0.250* (0.119)	-0.034 (0.051)
H	-0.002 (0.013)	0.241 (0.152)	0.058* (0.025)	0.009 (0.007)	0.084* (0.033)	0.022 (0.012)
$h(A_i/A^{\max})$	0.014 (0.013)	-0.014 (0.026)	-0.052* (0.025)	-0.003 (0.007)	-0.025 (0.015)	-0.012 (0.010)
Sample size	409	106	409	70	53	70
Instruments	40	27	40			
Countries	70	46	70			
AB AR(1)	-3.63**	-0.69	-3.45**			
AB AR(2)	-1.06	-1.12	-0.93			
Hansen: χ^2	40.29	10.80	44.68			

Note: Standard-errors in parentheses and *,** denote 5% and 1% level of significance. EDU is years of education estimates by Barro and Lee (2010), TIMSS is the TIMSS test scores, and SKILLS is the new latent index of education quality or cognitive skills. Following Krueger and Lindahl (2001), h stands for years of education and is equivalent to $\ln(H)$; In all regressions, we limited the number of instrument to lags 2-4 of h and $h(A_i/A^{\max})$ in order to avoid the problem of proliferation of instruments that can overfit endogenous variables (Roodman 2009a). AR(1) and AR(2) are Arellano-Bover tests for autocorrelation. Available on request are estimates of time effects.

Table 5. Translog Production Technology and Logistic Diffusion

Variables	System GMM (panel)			OLS Regression (cross-section)		
	EDU (1)	TIMSS (2)	SKILLS (3)	EDU (4)	TIMSS (5)	SKILLS (6)
Constant	-0.000 (0.043)	-1.400 (0.750)	-0.171* (0.070)	0.041 (0.025)	-0.125 (0.100)	-0.014 (0.036)
h	0.008 (0.010)	0.199* (0.100)	0.065** (0.024)	0.008 (0.006)	0.058* (0.029)	0.023** (0.008)
$h(A_i/A^{\max})$	0.004 (0.011)	-0.031 (0.031)	-0.042 (0.025)	-0.005 (0.006)	-0.025 (0.016)	-0.017* (0.007)
Sample size	409	106	409	70	53	70
Instruments	40	27	40			
Countries	70	46	70			
AB AR(1)	-4.15**	-0.03	-4.29**			
AB AR(2)	-1.60	0.03	-1.49			
Hansen: χ^2	31.79	10.21	29.30			

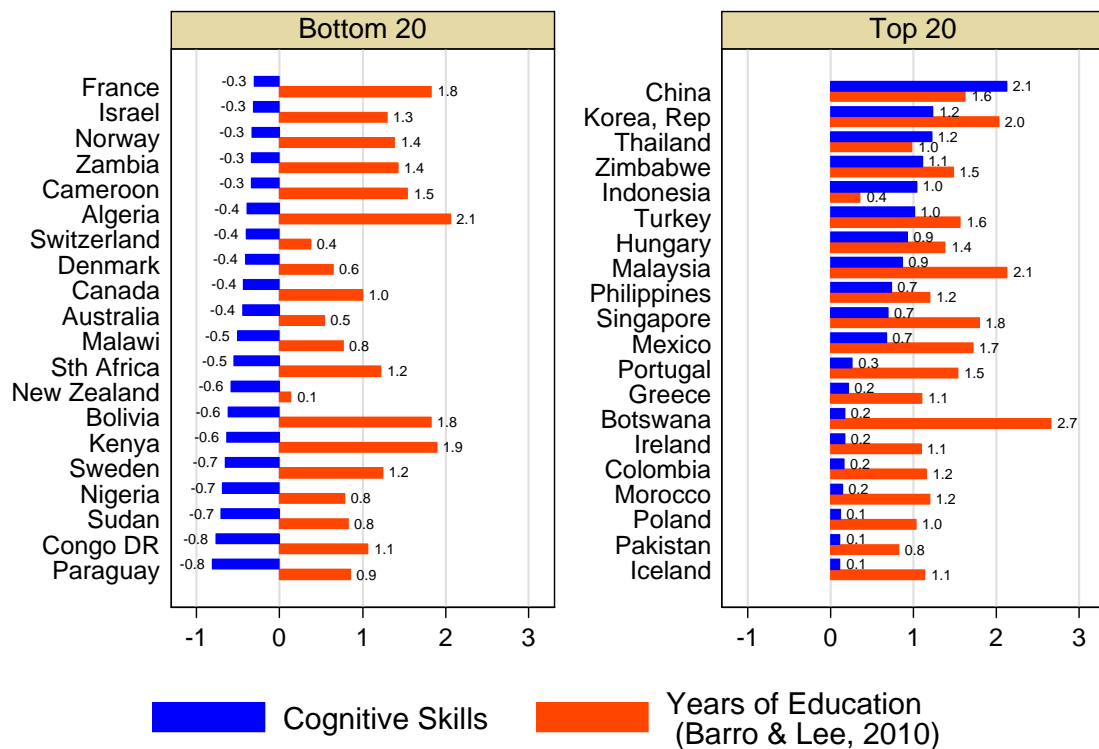
Note: Standard-errors in parentheses and *,** denote 5% and 1% level of significance. EDU is years of education estimates by Barro and Lee (2010), TIMSS is the TIMSS test scores, and SKILLS is the new latent index of education quality or cognitive skills. Following Krueger and Lindahl (2001), h stands for years of education and is equivalent to $\ln(H)$; In all regressions, we limited the number of instrument to lags 2-4 of h and $h(A_i/A^{\max})$. AR(1) and AR(2) are Arellano-Bover tests for autocorrelation. Available on request are estimates of time effects.

Table 6. Translog Technology, Complementarity and Skill Bias

Explanatory Variables	Quantile Regressions					
	1980-1984		1990-1994		2000-2003	
	Q25	Q75	Q25	Q75	Q25	Q75
Constant	(0.032)	-0.147*	-0.100	-0.035	-0.158	-0.090
	-0.063	(0.056)	(0.069)	(0.115)	(0.099)	(0.076)
ln(K/Y)	0.021	0.044**	0.054**	0.056*	0.060*	0.067**
	(0.013)	(0.014)	(0.017)	(0.023)	(0.026)	(0.016)
ln(W _S /W _N)	0.010	0.043	0.068**	0.072	0.108**	0.122**
	(0.019)	(0.027)	(0.025)	(0.045)	(0.040)	(0.040)
ln(Y/L)	-0.035	-0.064*	-0.074**	-0.083*	-0.105*	-0.091**
	(0.021)	(0.025)	(0.025)	(0.039)	(0.041)	(0.032)
ln(A)	0.071*	0.135**	0.136**	0.144**	0.193**	0.163**
	0.021	(0.041)	(0.036)	(0.048)	(0.056)	(0.045)
Observations	67	69	70	67	69	70
Pseudo R ²	0.25	0.49	0.36	0.43	0.41	0.43

Note: Standard-errors in parentheses and *,** denote 5% and 1% level of significance. Note, S in equation (12) is equal to $S=s*POP$ where s is the share of the population aged 25 years and over who have completed secondary schooling (Barro and Lee, 2010), and POP is total population.

Figure 1. Average Annual Change in Education and Skills, 1975-2003, (education



equivalent months)

Figure 2. Levels of Education and Cognitive Skills, 1970-2003, (education equivalent years)

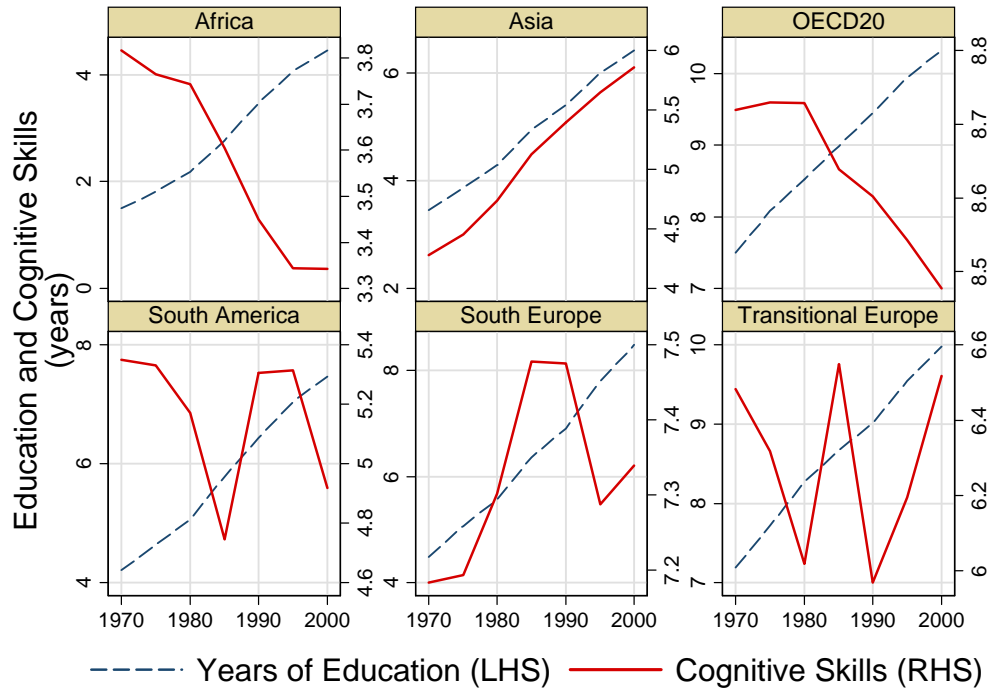
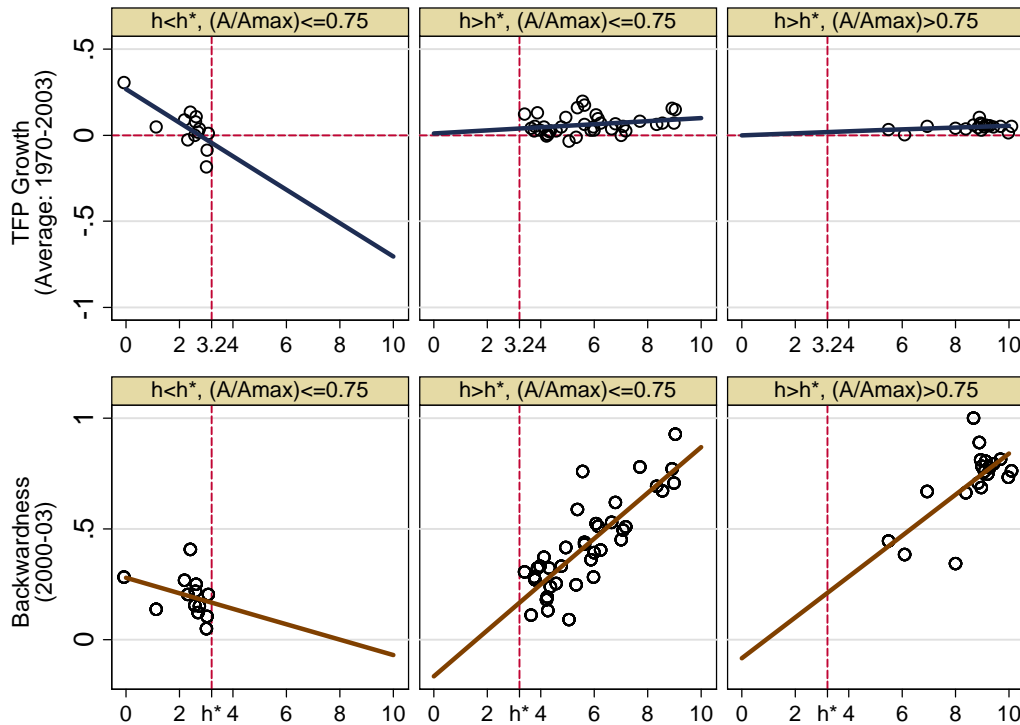


Figure 3. Cognitive Skills, Poverty Traps and Technology Diffusion, 1970-2003



Note: The USA was the technology leader in all periods. (A/A_{max}) is 'distance to the frontier' or backwardness in 1970 that ranges between zero and one, h is the cognitive skills measure of human capital, and h^* is the poverty trap threshold of human capital. There were 13 and 12 nations with human capital below h^* (equal to 3.2 and 3.1) in 1970-74 and 2000-03 respectively.