Valuable Skills, Human Capital and Technology Diffusion

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Abstract

This paper develops new estimates of human capital as a latent index of *valuable* skills for seventy countries over the period 1970-2003. The index is used to examine three models of technology diffusion and extend Benhabib and Spiegel (2005) to account for heterogeneity, complementarity between capital and skill (CSC) and skilled and unskilled labour (SNC), and skill-biased-technical-change (SBTC). The evidence shows that (1) the skills-education gap has widened in Africa, South America, Eastern Europe and most developed OECD countries; (2) skills facilitate innovation and technology diffusion; (3) the CSC, SNC and SBTC hypotheses are confirmed, and (4) international scientific collaboration greatly enhances the absorptive capacity of human capital.

Keywords: Human capital; Skills; Growth; Technology diffusion; CSC; SBTC

JEL Classification: J24, O10, O30, O40,

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1. Introduction

Since Schultz (1961), Becker (1964) and Romer (1990), human capital[1] is considered to be the engine of economic growth[2] in economics. Several hypotheses have been proposed to explain why human capital is important but 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 leads to the prediction that it is new investment in human capital that matters for economic 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. In terms of economic growth relations, the former school highlights the role of human capital accumulation while 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 technical progress can be understood as the process of new products development, and understanding how knowledge and skills contribute to this process can shed light on the introduction of new technologies. The idea draws on earlier insights on the link between R&D, innovation and market value in Schumpeter (1934) and Griliches (1981) and is central in the first generation of endogeneous growth models where human capital is the engine of innovation and sustainable growth (Romer 1990; Aghion and Howitt 1998).

Another idea highlights the importance of 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' or 'social capability' of the imitator (Wolff 2001; Falvey, Foster and Greenaway 2007). Here, 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

[1] Human capital is usually defined as the 'knowledge, skills, competencies and other attributes' that are relevant to economic activity (OECD 1998).

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

whereby less developed economies catch-up with the developed world.[3] The idea originates in Nelson and Phelps (1966) who assessed education to be a catalyst in the diffusion of new technologies. Their model rests on two key assumptions: the further an economy is from the technology frontier, the stronger is the incentive to exploit externalities; and the bigger the human capital the greater is the capability to learn and adopt the new technology.

Benhabib and Spiegel (1994) integrate the two ideas in a generalised model of human capital that aims to explain both innovation and technology diffusion. They build on the intuition that the two views of human capital are complementary rather than competing, 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 provided that educated workers “follow and understand new technological developments” (Nelson and Phelps 1966, p.69). Moreover, the hypothesis implies that a backward economy could overtake the technology leader by simply relying on investment in human capital.[5] As discussed in Benhabib and Spiegel (2005), this seems to ignore obstacles to free riding and limits to imitation. In particular, they contradict Schumpeter (1934) and current economic intuition that emphasise the role of intellectual property rights and innovation as a credible path to competitive advantage. This limitation also applies to Benhabib and Spiegel (1994) whose particular model also suggests that imitation can even dominate the benefits of innovation the further the country is from the frontier.

New evidence on the world distribution of income motivated further work in the assimilationist research program. First, the facts confirmed the view that, rather than factor accumulation, it is the Solow ‘residual’ or total factor productivity (hereafter TFP) that explained most of the cross-country differences in growth rates. Second, per

[3] The literature of ‘international spillovers’ have also considered FDI and trade as important channels of the transfer of knowledge; for details, see Coe and Helpman (1995), Rogers (1995) and Acharya and Keller (2007).

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

[5] This problem persists in other studies of the Nelson-Phelps hypothesis that replace the concept of “theoretical level of technology” (i.e., exogenously determined frontier technology) with that of technology in the leading country. An example is Dowrick and Rogers (2002).

capita incomes for a number of countries seemed to diverge rather than converge.[6] Third, substantial investment in education failed to protect less developed countries (LDCs) from stagnation (Pritchett 2001). In order to account for inconsistencies between theory and facts, Benhabib and Spiegel (2005) have revisited Benhabib and Spiegel (1994) to further extend the Nelson-Phelps hypothesis.[7] They consider a logistic diffusion process that acknowledges impediments to imitation and allows for divergence in world income. In their empirical application of their model, they find that logistic diffusion better explains world income growth patterns. Further, they are able to identify a number of countries that have been at risk of falling into poverty traps but this number appears to have diminished over time.

This paper contributes to the empirical literature of technology diffusion on three levels. First, it extends the approach of Dagum and Slottje (2000) to address the issue of unobservable human capital. It utilises TIMSS international test score data and *Web of Knowledge* data on scientific research output to obtain a new multi-dimensional index of human capital as a latent factor closely identified as “valuable cognitive skills”. This approach builds on three key insights: (a) human capital as an index of embodied knowledge is too rich to be captured by a single variable such as years of education (Le, Gibson and Oxley 2003; Dagum and Slottje 2000); (b) rather than skills, it is the *value* of skills that counts in economics (Schultz 1961: Becker 1964; Nelson 2005), and (c) given the scarcity of valid instruments,[8] the unobserved latent factor approach provides a solution to the endogeneity and measurement error problems (Heckman, Stixrud and Urzua 2006; Flossmann, Piatek and Wichert 2006).

Second, the paper deals with model uncertainty following Durlauf, Johnson and Temple (2005). More precisely, it explores three types of model uncertainty: (a) specification; (b) production technology,[9] and (c) parameter heterogeneity. On the first, this study compares three existing specifications of technology diffusion: Benhabib and Spiegel’s (1994) exponential diffusion; Dowrick and Rogers’ (2002) exponential diffusion with conditional convergence, and Benhabib and Spiegel’s (2005) logistic diffusion. In addition, it extends the logistic model in an attempt to go

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

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

[8] For further discussion of the issue, see Durlauf, Johnson and Temple (2005).

[9] We follow the convention of using the phrase “production technology” to refer to the form of the production function, in contrast to the term “technology” that stands for total factor productivity.

beyond the Cobb-Douglas production function of Benhabib and Spiegel (2005) to consider two alternative production technologies: the constant-elasticity of substitution (CES) production function of Duffy, Papageorgiou and Perez-Sebastian (2004), and the translog production function of Papageorgiou and Chmeralova (2005). These extensions are motivated by the proliferation of the literature on capital-skill complementarity (CSC) and skill-biased-technical-change (SBTC). The second is a more flexible approach and facilitates the differentiation between CSC and skill-biased-technology-change (SBTC). Note, however, that the principal objective here is to examine the robustness of Benhabib and Spiegel's (2005) logistic model within the framework of CES and translog production technologies. Furthermore, analysis here explores heterogeneity in the absorptive capacity of human capital by utilising new data on international research collaboration.

The third contribution of this paper is to extend the Benhabib and Spiegel (2005) model of logistic diffusion by employing dynamic panel data econometrics for two main reasons. First, it seems intuitive to utilise available information on the time-series data generating processes of the key variables explaining economic growth as a dynamic and causal relation. Second, panel data estimation techniques are advantageous in finite cross-sectional data when complemented with a methodology that minimises some of the limitations[10] associated with reverse causality, measurement errors and accounts for heterogeneity. This paper acknowledges that model heterogeneity may also arise in the technology diffusion process. Thus, it investigates the sensitivity of empirical estimates to non-arbitrary sub-groupings based on previous studies and theoretical predictions.

The rest of the paper is structured as follows. Section two presents the three alternative models of technology diffusion under examination. Section three presents the data used and outlines the adopted methodology regarding the estimation of human capital as a latent unobserved factor. The fourth section presents comparative estimation results for the three human capital models using three alternative estimation strategies in dealing with reverse causality in the human capital-growth relation. Section five extends analysis and estimation of the logistic model of Benhabib and Spiegel (2005) within the framework of capital-skill complementarities and the SBTC hypothesis. Section six summarises the new evidence and concludes.

[10] For a comprehensive review of growth econometrics, see Durlauf, Johnson and Temple (2005).

2. Methodology

Knowledge Diffusion: Three Models

In general, assimilation 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.

Below, we outline three models of technology diffusion as first proposed. For brevity, we drop the country indicator that is implicit. All three models assumed a Cobb-Douglas production function. 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. Technology interacts with human capital implying that technical change cannot be seen independently of human capital (i.e., the idea of human capital being the 'engine of growth' in new growth theories). 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 – in an endogenous growth framework, Benhabib and Spiegel (1994) specify technological progress, Δa, as:

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

Here, h_t is the natural logarithm of H_t, and g, m >0.[11] In this equation, the first term represents domestic innovation and the last tem is technological diffusion interpreted as the product of a country's level of human capital (i.e., absorptive capacity) and the

[11] 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.

gap between the technological level of a leading country, $A_t^{\max}$, and that of the home country, A_t, (this gap is also known by the terms "backwardness" and "distance to the frontier").[12] Benhabib and Spiegel (1994) take the log difference of (1) and substitute for (2) to arrive at the growth equation:

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

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.

The second model was proposed by Dowrick and Rogers (2002). It is different to Benhabib and Spiegel (1994) in three ways. First, human capital enters as a direct factor of production in (1). Second, the original Nelson and Phelps (1966) model of diffusion is adopted; i.e., the second term in (2). Finally, both endogeneous diffusion and neoclassical convergence are nested; that is, initial per worker output, y_0, enters as an independent factor. More formally, their empirical specification is of the type:

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

Dowrick and Rogers (2002) define y_t in per worker terms and Y_0 as per worker real GDP at the beginning of the period. The first two terms in (4) reflect two diverse sources of technological catch-up: neoclassical convergence to the steady state of *y*, and technology diffusion respectively. These sources compare with (2) in Benhabib and Spiegel (1994) who focus on domestic innovation and diffusion.

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[12] All original models take the USA to be the technology leader. We follow suit.

The third model examined here is the logistic model of diffusion proposed by Benhabib and Spiegel (2005). They modify (2) to allow for a greater human capital role in domestic innovation and 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 distance to the frontier due to technology clusters or an incompatibility with domestic technology or social values (Rogers 2005). More formerly, logistic diffusion takes the following form[13]:

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

Compared to the exponential model in (2), diffusion in (5) is moderated by the distance to the frontier, $(A/A^{\max})$. As a result, the innovation effect of human capital is 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: New Estimates

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 uni-dimensional measures are highly problematic in international panel data studies for several reasons.[14] First, they are poor indicators of education quality. Second, they ignore factors other than formal education that impact on skill formation. In addition, they often evolve in correlation with other macroeconomic variables that introduces

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[13] $\Delta a = (g + \frac{c}{s})h_t - \frac{c}{s}h_t(A_t / A_t^{\max})^s$ 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.

[14] 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.

endogeneity or reverse causality biases in estimation. Last but not least important, they fail to measure the value of education.[15]

Towards a multi-faceted measure of human capital, Hanushek and Kimko (2000) introduce school quality indicators in growth equations, as complementary to quantity measures. They find that international test scores of student achievement in mathematics and science are significant predictors of growth. Coulombe, Tremblay, and Marchand (2004) and Hanushek and Wößmann (2007) have confirmed the link between test scores and economic performance. According to Hanushek and Wößmann (2007), the cognitive skills deficit is greater in developing countries and quality indicators are less susceptible to estimation problems such as endogeneity, although recent evidence suggests that selection and endogeneity biases remain (Glewwe 2002; Galiani and Schargrodsky 2002; Paxson and Schady 2007).[16]

The search for improved multi-dimensional measures of human capital has moved in new directions. One involves the relaxation of the Nelson and Phelps (1966) assumption of education as the means to understanding and adopting new technologies. Thus, several papers explore the role of skill decomposition where primary or secondary education is more suitable for adoption and higher education is more appropriate for innovation (Acemoglu, Aghion and Zilibotti 2002; Ciccone and Papaioannou 2005; Vandenbussche, Aghion and Meghir 2006).[17] Jones and Schneider (2006) and Jones (2008), on the other hand, propose IQ test scores as a better measure of cognitive skills and abilities.

An alternative methodology invokes the Mincerian approach to human capital and seeks to decipher key insights[18]. So far, the literature has highlighted two principal ideas. One is that human capital is a composite index of skills acquired at school and skills learnt at work. Moreover, it is the current market value of these skills that counts as human capital. Although this micro approach focuses on *private* returns to education, the general methodology is employed here at the macro-level to account for both the quality and value of human capital.

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[15] These problems have been well documented in OECD (1998; 2000), Bils and Klenow (2000), Wößmann (2003), Le, Gibson and Oxley (2003), Abowd *et al.* (2005).

[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".

[17] Hanushek and Wößmann (2007) and the skill decomposition approach are two alternative interpretations of why higher education failed to translate into growth in LDCs (Pritchett 2001).

[18] This is the approach adopted in Krueger and Lindahl (2001), Abowd *et al.* (2005) and Piekkola (2006). See also OECD (1998) and Sianesi and van Reenen (2003) for extensive surveys of alternative methodologies in the measurement of human capital.

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 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 individuals to participate in current markets and adapt to change (Lanzi 2007). Another expression 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 and workplace learning (Borghans and Heijke 2005; Nordman and Wolff 2007; Destre, Levy-Garboua and Solloboub 2007; Robst 2007).

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

A New Human Capital Index

The case 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, Stixrud and Urzua 2006; and Flossmann, Piatek and Wichert 2006); (c) skill obsolescence (Alders 2005; Gorlich and de Grip 2007; Pfeiffer and Reuß 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[19].

We maintain that the approach is particularly suitable for the task of integrating the education quality literature and the market value perspective of human capital. The debate about quality vs. value is equivalent to the search for a measure of patent quality in the innovation literature. Lanjouw and Schankerman (2004) settle the issue with a composite index of patent quality that measure both “the technological and value dimensions of an innovation”. We adapt the Lanjouw and Schankerman (2004) approach to associate “quality of education” with “valuable skills” in order to highlight the importance of “cognitive skills” and the market “value” of education.

In particular, we adapt Hanushek and Kimko (2000), and Dagum and Slottje (2000) to obtain new estimates of human capital as a latent factor identifiable as “valuable cognitive skills”. We first draw on Hanushek and Kimko (2000) who a 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) on the other hand estimate human capital as a latent variable using indicators available in household survey data. Unfortunately, none of these indicators are direct measures of intelligence or education quality (Le, Gibson and Oxley 2003, p.293).

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

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

$I_{k,jt}$ is the log of indicator k of country j at time t, h^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 education quality that impacts on all the following indicators: imputed test scores (*TS*), per capital scientific publications in science (*SciP*), per capita capital equipment (*Ke*), and per capita manufactured exports (*Xm*); the Data Appendix has full details on the sources and definitions of all variables used in this study. The use of TIMSS as a proxy for cognitive skills has been established in the literature cited earlier. It also seems intuitive that our bibliometrics measure, *SciP*,

[19] See, for instance, Temple (1999), Durlauf, Johnson and Temple (2005), and Heckman, Stixrud and Urzua (2006).

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. Our capital equipment variable is also based on existing literature linking equipment investment to relative wages and skilled labour (Karnit and Hercowitz 2000). Finally, the literature also suggests that exports and manufactured goods are key indicators of "skills and know-how"[20].

First, we extend Hanushek and Kimko (2000) to obtain imputed test scores, *TS*, in panel regressions that control for heterogeneity. Table 1 presents the results of feasible GLS estimates of the log of TIMSS scores[21] against the log of secondary education attainment rates (Barro and Lee 2001), the log of infant mortality rates, the log of labour participation rates, time effects, and a constant. *TS* is critical for the identification of the common factor as a measure of cognitive skill, secondary education is intended to capture the effect of parental and public education on student test performance. We also use infant mortality rates on the basis of Fortson (2008) who shows that mortality risk reduces the returns to education due to life uncertainty and thus, serves as a disincentive to investing in skills.

Table 1. Modelling TIMSS, Panel Estimation

Variables	
Constant	6.427* (0.063)
ln**(SECO)**	0.059* (0.013)
ln**(MORTAL)**	-0.107* (0.008)
ln**(LPR)**	0.427* (0.062)
Time (1980-1984)	0.673* (0.031)
Time (1985-1989)	0.575* (0.036)
Time (1990-1994)	0.803* (0.027)
Time (1995-1999)	0.458* (0.026)
Time (2000-2003)	0.415* (0.025)
Observations	122
LR χ^2	2121.55*

Note**:** Standard-errors in parentheses. * denotes 5% level of significance. SECO is secondary education attainment; MORTAL is infant mortality; LPR is labour participation rate.

[20] Kaldor (1962, p.495) but also see Domeland (2007) and Fryges and Wagner (2007).

[21] 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.

The coefficient estimates in Table 1 were then used to impute the value of *TIMSS* for all countries and proceed to estimate h^S by means of factor analysis that allows for two latent factors. The findings are summarised in Table 2 by period. They show that (a) the factor loadings are high and increasing over time; (b) the "scores" suggest that the weight of both cognitive skills and scientific publications was 52% in 1970-74 but declined to 46% in 2000-03; (c) capital equipment increased its weight from 27% to 30% over the same period; (d) the Kaiser-Meyer-Olkin statistic points to a high sampling adequacy of the model; (e) the eigenvalue estimates led us to reject the null hypothesis of two latent factors but not that of one factor, and (f) the model explains 84% to 91% of the total variation. We name this single latent variable "valuable skills" or "education quality" given the employment of both *TIMSS* and *SciP* that clearly associate with cognitive skills.

Table 2. Human Capital as a Latent Factor: Factor Analysis

Panel A		Indicators				Eigenvalue by Factor		Explained Variation	Sample Size
		TS	**SciP**	**Ke**	**Xm**	F 1	F 2	F 1	
1970-1974	Loadings	0.90	0.92	0.91	0.93	3.35	0.31	0.84	62
	Scores	0.22	0.30	0.27	0.31				
	KMO	0.86	0.84	0.83	0.82				
1975-1979	Loadings	0.89	0.90	0.93	0.94	3.35	0.29	0.84	64
	Scores	0.19	0.22	0.31	0.37				
	KMO	0.88	0.89	0.80	0.79				
1980-1984	Loadings	0.90	0.93	0.93	0.96	3.45	0.26	0.86	67
	Scores	0.17	0.23	0.27	0.40				
	KMO	0.88	0.89	0.82	0.79				
1985-1989	Loadings	0.92	0.94	0.94	0.94	3.49	0.22	0.87	67
	Scores	0.22	0.28	0.31	0.27				
	KMO	0.87	0.85	0.82	0.85				
1990-1994	Loadings	0.93	0.94	0.96	0.95	3.58	0.20	0.89	67
	Scores	0.20	0.23	0.33	0.30				
	KMO	0.88	0.87	0.79	0.81				
1995-1999	Loadings	0.94	0.94	0.96	0.96	3.62	0.16	0.90	69
	Scores	0.22	0.20	0.30	0.32				
	KMO	0.90	0.91	0.84	0.83				
2000-2003	Loadings	0.95	0.94	0.96	0.96	3.62	0.16	0.91	70
	Scores	0.25	0.21	0.30	0.28				
	KMO	0.89	0.90	0.85	0.85				

Note: TS is the test scores predicted (TIMSS), SciP is per capita scientific publications in sciences, Ke is per capita capital equipment stock and *Xm* is per capita manufactured exports. All four are in logs. KMO statistic is the Kaiser-Meyer-Olkin measure of sampling adequacy. Not reported here, the KMOs test for the overall model ranged from 0.83 (min) to 0.87 (max).

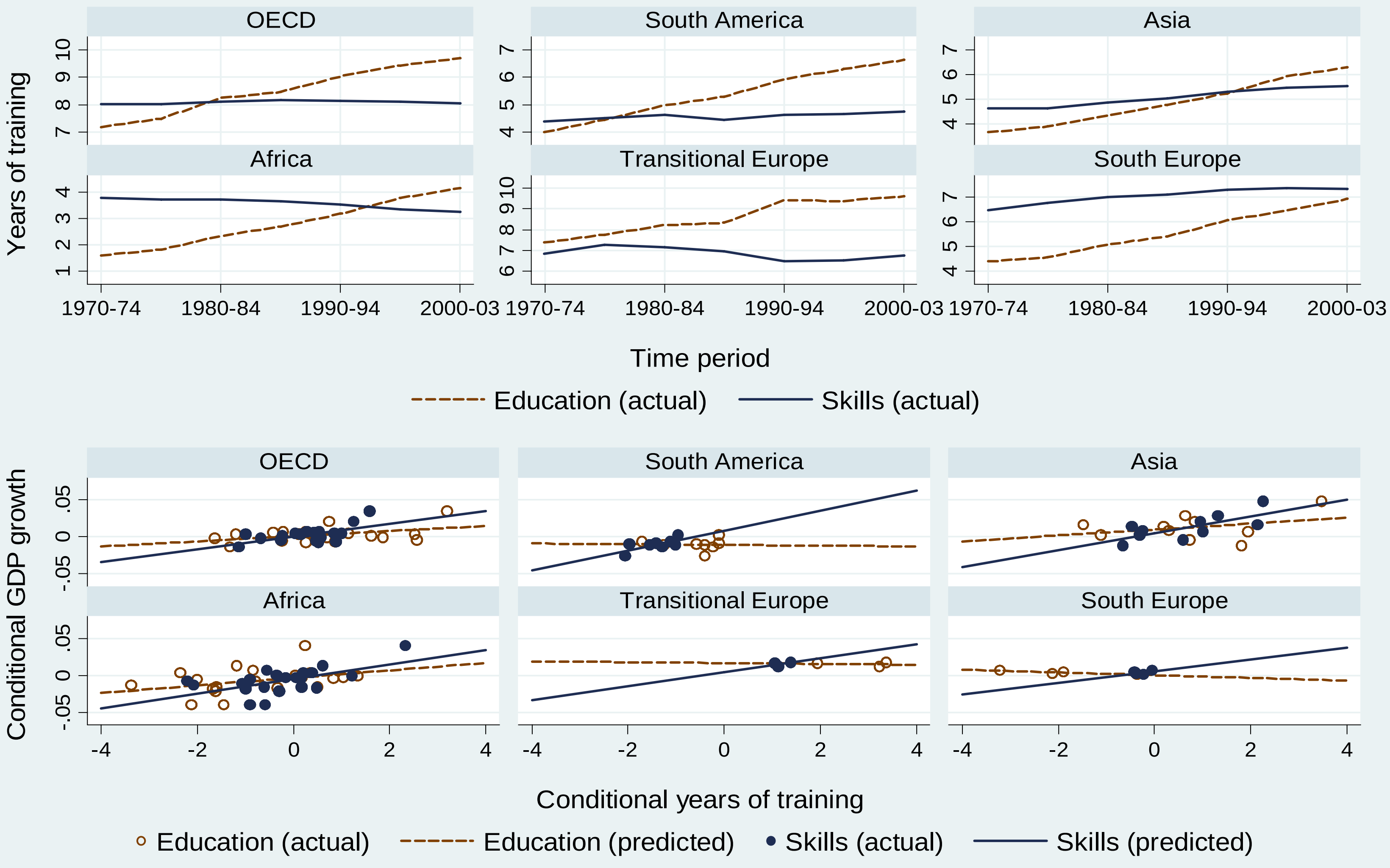
Figure 1, top panel, presents the two measures of human capital used in this study for six regional groups: OECD countries, South America, Asia (excluding Japan and South Korea), Africa, transitional economies in Europe and South Europe[22]. The first is Barro and Lee's (2001) education attainment measure extended to 2003, the second is the new index of education quantity[23]. The results confirm the Hanushek and Wößmann (2007) finding of skills deficit in developing economics. In contrast, however, the new index of human capital indicates that the quality of education has declined in Africa and East Europe, has changed little in the OECD and South America, and has improved substantially in Asia and South Europe. Education attainment, on the other hand, has surged in most regions.

The lower panel of Figure 1 depicts years of education quantity and quality (i.e., skills) conditional on the log of real per capital GDP in 1970 against conditional average GDP growth as cited in Hanushek and Wößmann (2007). The chart displays an ambiguous relation between education quantity and GDP growth but a consistently positive relation between education quality and growth. Moreover, the latter exhibits a regression slope that is much higher than that of the former, a result consistent with Hanushek and Wößmann (2007). Note, however, our measure of education quality is the unobserved *market value* of cognitive skills.

[22] These are Austria, Australia, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Korea, Mexico, Netherlands, NZ, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, UK and the USA. Italy, Greece, Portugal and Turkey form the "South Europe" group.

[23] See the Data Appendix for details. Note also that, for comparability, h^S was rescaled to be the predicted value of education attainment in a robust generalized LS panel (FGLS) regression with a constant and the original h^S scores as regressors. Lane (2002) shows that GLS estimation minimises the bias in random variable transformations.

Figure 1. Education and Valuable Skills, 1970-2003



Note: Conditional values are residuals of cross-section regressions of each variable (averages) on the log of per capita real GDP in 1970. Predicted values of TIMSS and IQ tests scores are available upon request. IQ data are from Lynn and Vanhanen (2002). The “South Europe” group consists of Italy, Greece, Portugal and Turkey and is a subset of OECD group. For transitional economies, only for Hungary, Poland and Romania there are data since 1970.

Panel Estimation Results

This study utilises Penn World Tables, World Development Indicators and Barro and Lee (2001) data to extend the latter to 2003 as per Kyriacou (1991). These assist in the estimation of the three models of technology diffusion outlined above. First, for comparison with previous studies, we use average years of education as a proxy for human capital. We employ the two-step *System GMM* panel estimator of Arellano and Arellano and Bover (1995)[24]. In columns 1-3 in Table 3 there are estimates of the above three models when lagged variables are used to control for endogeneity. Since distance to frontier[25] correlates with lags of the dependent variable, we follow Acemoglu, Aghion and Zilibotti (2002) to also instrument technology diffusion. The results seem to validate the first two models but coefficient estimates for the Benhabib and Spiegel (2005)[26] model have the wrong sign and are not statistically significant. The last three columns repeat the estimation procedure using an alternative set of instruments for human capital and the interaction term of the diffusion process. These are lagged values of the exports share of manufactured goods, of the log of the population share of urban labour force, and the log of infant mortality rates. Again the results are similar to those in columns 1-3 but now the classical convergence coefficient is insignificant in the Dowrick and Rogers (2002) model.

Next, we re-estimate the three models by employing the new latent factor as a measure of human capital. We still account for the possibility that this new index may be endogenous by using instruments for human capital, technology diffusion as well as other variables as per Table 3. Table 4 reports the estimation results that suggest that human capital facilitates technology diffusion. Yet, the estimates in columns 1-2 cast doubt on the validity of the models proposed by Benhabib and Spiegel (1994) and

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[24] The "xtabond2" procedure of Roodman (2006) was employed with a finite-sample correction, following Windmeijer (2005) who shows that the correction improves the efficiency of the two-step robust GMM estimator.

[25] This is defined as (Y^{max}/Y) in Benhabib and Spiegel (1994), $\ln(Y^{max}/Y)$ in Dowrick and Rogers (2002), and (A/A^{max}) in Benhabib and Spiegel (2005).

[26] 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., $\ln(A_t) = \ln(Y_t) - (1/3)\ln(K_t) - (2/3)\ln(L_t)$. Note that we also run cross-section regressions as in Benhabib and Spiegel (2005) using 1970, average and conditional on 1970 values for human capital. Only when conditional values were used we obtained significant coefficient estimates for h and $h*\ln(A/A^{max})$. Respectively, these were 0.036 (0.011) and -0.054 (0.019) for education and 0.057 (0.015) and -0.057 (0.029) for skills, robust standard errors in parentheses.

Dowrick and Rogers (2002). In the first model, the g_k and h*(Y^{max}/Y) coefficients are not statistically significant while it is ln(y_0) and h*ln(Y^{max}/Y) that are not statistically significant in the second model. Column three provides generalized LS panel estimates (FGLS) for the Benhabib and Spiegel (2005) model.

Table 3. Education and Growth: System Panel GMM

	Instruments Set A			**Instruments Set B**		
Explanatory Variables	**(1A) BS (1994)**	**(2A) DR (2002)**	**(3A) BS (2005)**	**(1A) BS (1994)**	**(2A) DR (2002)**	**(3A) BS (2005)**
Constant	0.211		-0.088	-0.097		0.072
	(0.166)		(0.053)	(0.117)		(0.014)
ln(Y_0)		-0.002*			-0.0007	
		(0.001)			(0.005)	
Δh		0.024*			0.008	
		(0.011)			(0.009)	
Δk	0.405*	0.345*		0.601*	0.547*	
	(0.116)	(0.138)		(0.139)	(0.115)	
Δl	0.649			-0.131		
	(0.419)			(0.282)		
h	0.008*		-0.009	0.004*		-0.016
	(0.002)		(0.008)	(0.001)		(0.014)
h*(Y^{max}/Y)	0.0004*			0.0003*		
	(0.001)			(0.0001)		
h*ln(Y^{max}/Y)		0.001*			0.0008*	
		(0.000)			(0.0003)	
h*(A/A^{max})			0.009			0.023
			(0.007)			(0.014)
Observations	405	404	409	405	404	407
AB AR(1)	-2.48*	-0.82	-2.65*	-0.94	-0.05	-2.82*
AB AR(2)	-1.18	-1.37	-1.25	-1.18	-1.97	-1.53
Hansen: χ^2	9.12	15.30	35.91	7.78	46.25	24.79

Note**:** BS (1994), DR (2002) and BS (2005) stand for Benhabib & Spiegel (1994), Dowrick and Rogers (2002) and Benhabib & Spiegel (2005) respectively. Standard-errors in parentheses. * denotes 5% level of significance. Following Krueger and Lindahl (2001), *h* is equivalent to ln(*H*) and stands for years of education, although Benhabib and Spiegel (2005) define *h* as the natural log of years of education. For instruments, we used lags 2 and above for ln(y), g_k, H and the interaction term plus one lag of g_n. Not reported here, Hansen tests of exogeneity of instruments do not reject the null hypothesis in all GMM regressions. All panel regressions include time effects, estimates are available on request.

As expected, the coefficient estimate of *h* is positive and that of h*(Y/Y^{max}) is negative, although only the former is statistically significant. These compare with system panel GMM estimates in column four. Interestingly, the size of the FGLS estimate is similar to that reported in column three of Table 3 but the GMM estimates indicate a larger human capital effect on TFP growth. Table 4 also reports Hansen tests of over-identifying restrictions. These do not reject the null hypothesis of valid instruments.

In column five of Table 4, we relax the assumption of a homogeneous human capital effect in view of Vandenbussche, Aghion and Meghir (2006) Aghion and Howitt (2006) who emphasise compositional effects and Falvey, Foster and Greenaway (2007) who find that absorptive capacity is far more important than distance to the frontier in technology diffusion. Thus, there are reasons to suspect that the composition of human capital matters in knowledge diffusion. One invokes the role of tacit knowledge as complementary to codified knowledge (OECD 2000; Howells 2002; Nelson 2005). Lenger and Taymaz (2006) show that labour mobility involving foreign firms is the main channel of technology transfer from abroad in Turkish manufacturing. Although they interpret this finding in terms of tacit knowledge effects, the evidence is also consistent with alternative paths to learning, such as networks emphasised in the innovation and sociology literature (Rogers 2005; Pelc 2007). According to Granovetter (2005, p.46), Schumpeter's definition of entrepreneurship involves new combinations of "previously unconnected resources for a new economic purpose" and "one reason resources may be unconnected is that they reside in separated networks of individuals or transactions".

We focus on the quality of higher education and the most skilled workers. We utilise ISI *Web of Knowledge* bibliometrics data since 1973 to construct a series that measures a country's collaborative scientific research productivity, CoS_t[27]. We take the mean of this series in period *t* as a threshold value, c, to construct an indicator variable, *R*, that takes the value of one for values above the mean and zero for values below. More formally, we modify (5) to formulate technological progress as follows:

$$\Delta a_t = \left[(g_0 + m_0)h_t - m_0 h_t D_t\right]\left(1 - R_t\right) + \left[(g_1 + m_1)h_t - m_1 h_t D_t\right] R_t + e_t \qquad (7)$$

where D_t is distance to the frontier, equal to (A/A^{max}), $R[CoS_t>c]$ is the threshold indicator and e_t is an error term.

[27] Research productivity, *CoS*, was defined as the number of journal articles in science in at the beginning of the period per real GDP when at least one of the co-authors resided in one of the following 16 OECD countries: Australia, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, Norway, Spain, Sweden, Switzerland, UK and the USA.

Table 4. Quality of Education and Growth: Panel FGLS and System GMM

Explanatory Variables	BS (1994) GMM (1)	DR (2002) GMM (2)	Benhabib and Spiegel (2005) FGLS (3A)	System GMM (3B)	(3C)
Constant	0.267		0.004	-0.105*	-0.074
	(0.236)		(0.015)	(0.049)	(0.054)
$\ln(Y_0)$		-0.0003			
		(0.0006)			
Δh		0.002			
		(0.016)			
Δk	0.118	0.406*			
	(0.178)	(0.204)			
Δl	0.715*				
	(0.581)				
h	0.007*		0.010*	0.044*	
	(0.003)		(0.004)	(0.014)	
h(1-R)					0.022
					(0.023)
hR					0.043*
					(0.013)
$h^*(Y^{max}/Y)$	0.001				
	(0.001)				
$h^*\ln(Y^{max}/Y)$		0.0018			
		(0.0011)			
$h^*(A/A^{max})$			-0.004	-0.030*	
			(0.003)	(0.012)	
$h^*(A/A^{max})$ (1-R)					0.016
					(0.029)
$h^*(A/A^{max})$ R					-0.037*
					(0.012)
Observations	396	396	404	404	404
AB AR(1)	-1.98*	0.68		2.64*	-2.77*
AB AR(2)	-0.57	-1.45		0.36	0.79
Hansen: χ^2	37.97	48.08		32.87	43.35

Note**:** BS (1994) and DR (2002) stand for Benhabib and Spiegel (1994) and Dowrick and Rogers (2002) respectively. *R* is an indicator variable being equal to one if CoS_t>mean(CoS_t) and equal to zero otherwise. In parentheses are standard-errors and * denotes 5% level of significance. As in Table 3, *h* is equivalent to ln(*H*) and stands for years of education. More details are in notes to Table 3. Not reported here, Hansen tests of exogeneity of instruments do not reject the null hypothesis in all GMM regressions. All panel regressions include time effects, estimates are available on request.

The panel GMM results appear in column five in Table 4. These clearly show that international scientific collaboration is a catalytic factor in technology diffusion. Countries with below average collaborative research output fail to utilise their human capital towards domestic innovation and, more importantly, they are unable to adopt foreign technology. More specifically, only nations where scientists collaborate with other scientists from advanced OECD economies can achieve TFP growth in the order of 4.3% per year of quality education. Moreover, 86% of this growth is due to the technology diffusion process (i.e., 0.037 as a percentage of 0.043).

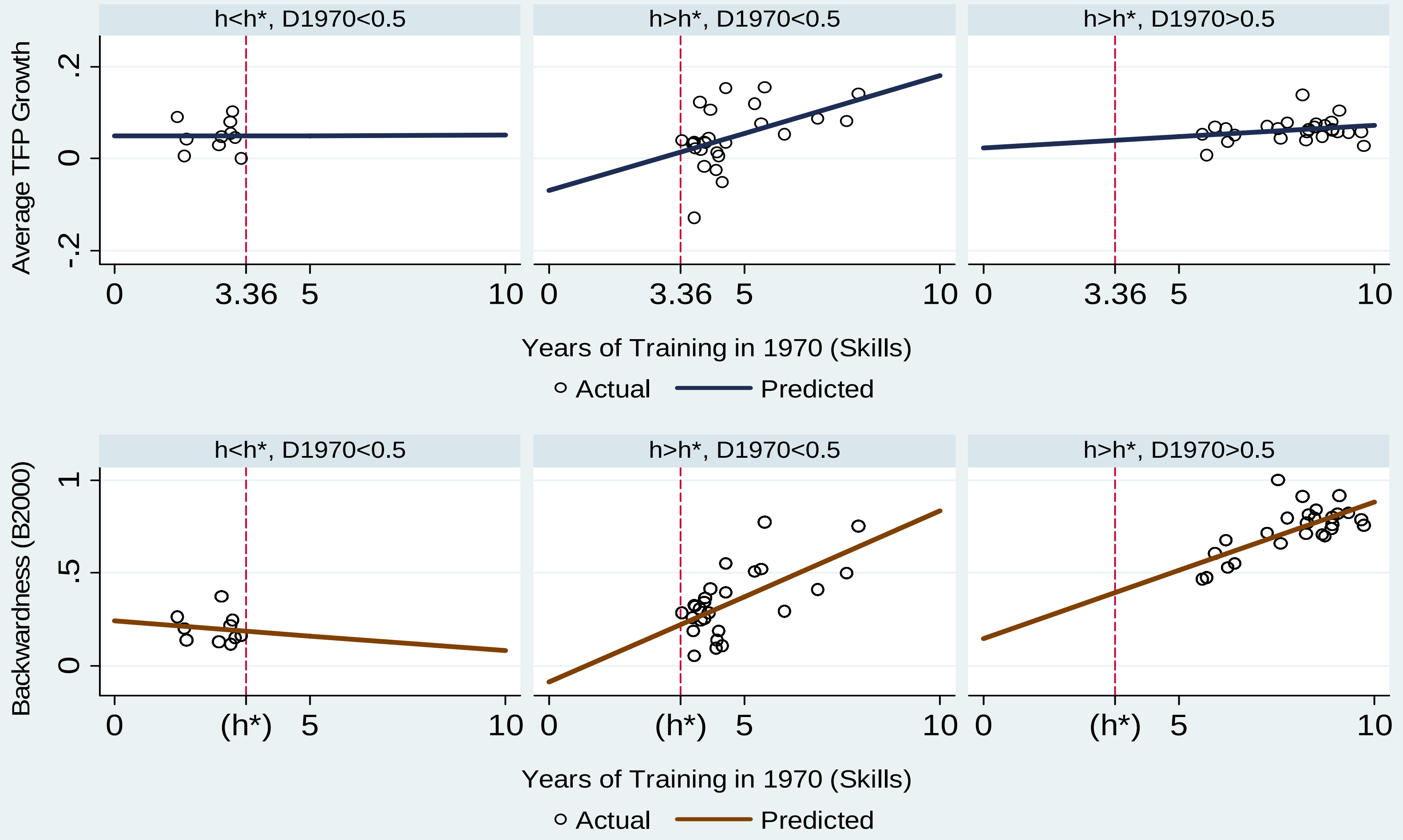
Benhabib and Spiegel (2005) also explore the implications of the logistic diffusion process for developing nations and their capacity to catch up with the developed economies. That capacity, they argue, depends on a critical threshold level of human capital. Nations with human capital levels below that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

$$h_t^* = \exp\left(\frac{sg\ln(h_t^{\max})}{sg+m}\right) \tag{8}$$

In the case of logistic diffusion, s=1 (see footnote 13 above), $h_t^{\max}$ is human capital in the leading country in period t, and g and m are estimates of the human capital stock and diffusion parameters in model (5). Benhabib and Spiegel (2005) use average years of education as a proxy for human capital and estimate h* to be 1.78 in 1960, and 1.95 in 1995. In 1960 there were 27 countries with actual years of education being below the threshold. By 1995, the corresponding number had declined to 4.

We emulate this exercise using our new index of "valuable skills" as a measure of human capital and the empirical estimates in column four in Table 4. Figure 2 summarises the results by human capital and distance to the frontier, D1970, in 1970. Three country groups are available. The first consists of nations with more than 50% distance from the leader (i.e., the USA) and with human capital below the threshold value of 3.36 in 1970. The top panel clearly illustrates the fact that economies that failed to meet the above "catch-up condition" were unable to experience TFP productivity growth since 1975 (top left). On the other, hand, countries far from the frontier and with a skills level that meets condition (8), they grow faster than other countries (see top centre). Consequently, economies that remain stagnant fail to catch-up and find themselves further away from the USA in 2000 (bottom left). In contrast, nations that were far from the frontier but with enough skills in 1970, they improved their position substantially as they invested in skills since 1970 (bottom centre).

Figure 2. Skills, Backwardness and TFP Growth, 1970-2000



Note: D1970 and D2000 stand for "distance to the frontier" of level of backwardness in 1970 and 2000 respectively, defined as the ratio of (A/A^{max}). A^{max} and h* are TFP in the leader country and the human capital threshold respectively, as defined in Benhabib and Spiegel (2005). There were no countries with h<h* and D1970>0.5 or with h>h* and D1970<0.5. In ascending order of h, in 1970 the group in far left corner consists of Indonesia, Uganda, Ethiopia, Sudan, Colombia, Pakistan, Malawi, India, Tanzania and Nigeria. In 2000, the corresponding group had expanded to 15 countries. It excluded Indonesia, Colombia and Pakistan but included Sierra Leone, Senegal, Zaire, Cameroon, Kenya and Zimbabwe. The minimum values of D1970 and D2000 were 0.095 and 0.05 respectively.

Using the new index of human capital, we find there were ten countries that were unable to meet condition (8) in 1970. This number, however, increased to 15 in 2000[28]. This finding contrasts with that of Benhabib and Spiegel (2005) reported above and calls for greater attention to skills in development policy. This is consistent with the evidence in Hulten and Isaksson (2007) who find that the gap between rich and poor is likely to persist.

4. Skill-Capital Complementarity and SBTC

In recent times, empirical research has cast doubt on the validity of Cobb-Douglas production functions in understanding long-term growth patterns. Moreover, there is mounting evidence in favour of a production technology that acknowledges capital-skill complementarities (CSC) and/or skill-biased-technical-change (SBTC)[29]. Nelson and Phelps (1966) briefly discussed the former. Benhabib and Spiegel (1994, 2005) also considered the CSC hypothesis but never abandoned Cobb Douglas technology.

In this section, we seek to test the robustness of the logistic diffusion model (5) by examining alternative production technologies that allow for CSC and/or SBTC. This is particularly important in the light of Lopez-Pueyo, Barcenilla and Sanau (2008) who show that the choice of a production and, thus, the way TFP is calculated is critical for the identification of knowledge spillovers. Furthermore, we wish to examine whether the results in Table 4 stand when we account for CSC and SBTC, especially in view of the link between skills and human capital.

CES Production Technology: Calibration

First, we revisit the Benhabib and Spiegel (2005) model of logistic diffusion to consider the CSC hypothesis. We adopt the two-level CES production function of Duffy, Papageorgiou and Perez-Sebastian (2004). In contrast to this study, we allow

[28] While Asia was represented by Indonesia, India and Pakistan in 1970, only India had remained in the “poverty trap” group in 2000; Africa’s share increased from six to fourteen. For further details, see notes to Figure 2.

[29] Seminal papers are Krusell *et al.* (2000), Acemoglu and Zilibotti (2001), Duffy, Papageorgiou and Perez-Sebastian (2004), Caselli (2005), Papageorgiou and Chmeralova (2005), and Kneller and Stevens (2006).

for endogeneous TFP, A, as proposed by Benhabib and Spiegel (2005). More formally, we define the log of TFP, a_t, as follows

$$a_t = y_t - (1/\rho)\ln\left\{a\left[(bK_t^{\theta} + (1-b)S_t^{\theta}\right]^{\rho/\theta} + (1-a)N_t^{\rho}\right\} + e_t \tag{9}$$

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. In order to evaluate the Benhabib and Spiegel (2005) model, we calibrate (9) on the basis of evidence in Krusell *et al.* (2000); i.e., we set a=1/3, b=0.5, θ=-0.4 and ρ=0.5. Note also that, S is defined as the proportion of the labour force having completed primary education[30] and N is the residual labour force.

Duffy, Papageorgiou and Perez-Sebastian (2004) ponder about the definition of skilled labour, S, and experiment with various measures. Here, we report results using two different thresholds. The first uses Barro and Lee's (2001) measure of primary school attainment (PRIM) since it is consistent with evidence of CSC in Duffy, Papageorgiou and Perez-Sebastian (2004), and facilitates comparison with the translog model below. Panel 1 in Table 5 presents the results. Column one has GLS panel estimates. The coefficients appear with the right signs and are statistically significant, except that they are now higher than those observed in column three in Table 4. Column two has the GMM estimates that compare with those in column two in Table 4. Again, the coefficients are statistically significant, have the right sign but the coefficients for h_i and $h_i(A_i/A^{max})$ are much higher than the corresponding estimates in Table 4. In column three of Table 5, there are GMM estimates for the threshold model (7). Once again, the role of scientific collaboration as a catalyst in absorptive capacity is confirmed: only in countries where the catch-up condition (8) is satisfied, we observe significant diffusion effects. The results in Table 5 also contrast with those in Table 4 with respect to the impact of human capital on domestic innovation. Under CES production, the coefficient of h_i is much higher than the one

[30] We also used the Barro and Lee (2001) measure of the share of population that had completed post-secondary education as an alternative threshold. Regression estimate results were similar to those obtained here and are available on request.

under Cobb-Douglas production in Table 4. Moreover, under CES and CSC, human capital assists domestic innovation even when scientific collaboration is weak.

An alternative definition of skilled labour, S, used here is the latent index of skills standardised to be in the range [0, 1], labelled as H_S. Panel 2 in Table 5 presents the results of this approach. The estimates here are very similar to those in the columns 1-3 in Table5. The only difference is that the effect of research collaboration has a smaller but still important effect on local innovation and technology diffusion.

Thus, we conclude that the human capital effect on diffusion and TFP growth does not appear to derive from a neglect of capital-skill complementary in production. Yet, we reserve judgment until we consider an alternative account of CSC that simultaneously allows for skill bias in technology change.

Table 5. CES Technology and Benhabib & Spiegel (2005): Panel Estimation

	Panel 1: Primary School			**Panel 2**: Valuable Skills		
Explanatory	**FGLS**	**GMM**		**FGLS**	**GMM**	
Variables	**(1A)**	**(1B)**	**(1C)**	**(2A)**	**(2B)**	**(2C)**
Constant	0.069*	-0.086	-0.056	0.057*	-0.094	-0.150
	(0.022)	(0.078)	(0.065)	(0.024)	(0.082)	(0.098)
h	0.025*	0.061*		0.028*	0.062*	
	(0.005)	(0.020)		(0.005)	(0.019)	
h(1-R)			0.056*			0.071*
			(0.019)			(0.026)
hR			0.060*			0.070*
			(0.013)			(0.023)
h*(A/A^{max})	-0.012*	-0.043*		-0.012*	-0.032*	
	(0.004)	(0.019)		(0.004)	(0.015)	
h*(A/A^{max}) (1-R)			-0.018			-0.017
			(0.030)			(0.030)
h*(A/A^{max}) R			-0.046*			-0.047*
			(0.014)			(0.016)
Observations	402	402	402	402	402	402
AB AR(1)		-3.30*	-3.35*		3.50*	3.78*
AB AR(2)		1.94	1.86		1.68	1.88
Hansen: χ^2		31.51	53.41		32.68	42.15

Note**:** In parentheses are standard-errors and * denotes 5% level of significance. *h* denotes years of education and is equal to ln(*H*). More details are in notes to Table 3. Not reported here, Hansen tests of exogeneity of instruments do not reject the null hypothesis in all GMM regressions. All panel regressions include time effects, estimates are available on request. R is an indicator variable being equal to one if CoS_t>mean(CoS_t) and equal to zero otherwise.

Translog Production Technology: Calibration

The translog production function is a more flexible functional form that allows one 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 allow for technology in the translog variable cost function:

$$\begin{aligned} \ln C = {} & \alpha_0 + \alpha_Y \ln Y + \sum_i \alpha_i \ln W_i + \alpha_K \ln K + \alpha_A \ln A + \alpha_{YK} \ln Y \ln K + \\ & \frac{1}{2}\left(\alpha_{YY} (\ln Y)^2 + \sum_i \sum_j \alpha_i \ln W_i \ln W_j + \alpha_{KK} (\ln K)^2 + \alpha_{AA} (\ln A)^2 \right) + \\ & \frac{1}{2}\left(\sum_i \sum_j \rho_{ij} \ln W_i \ln K_j + \alpha_{AA} (\ln A)^2 + \sum_j \rho_{Yi} \ln Y \ln W_i \right) + \alpha_{AK} \ln A \ln K \end{aligned} \tag{10}$$

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:

$$\Theta_S = \frac{\partial \ln C}{\partial \ln P_S} = \alpha_S + \alpha_Y \ln Y + \sum_j \gamma_{Sj} \ln W_j + \alpha_K \ln K + \alpha_A \ln A \tag{11}$$

Assuming homogeneity of degree one in variable input prices (i.e., $\gamma_{S} + \gamma_{N} = 0$) we have

$$\Theta_S = \alpha_S + \gamma_K \ln(K/Y) + \gamma_S \ln(W_S / W_N) + \gamma_Y \ln Y + \gamma_A \ln A \tag{12}$$

Model (12) 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, Y, and technology, A. 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) and assuming constant returns to scale, TFP can be expressed as

$$\ln A = \ln Y - \left[\alpha \ln(K) + (1-\alpha)\left(\Theta_S \ln(S) + (1-\Theta_S)\ln(N)\right)\right] \tag{13}$$

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 in our sample[31], and (c) calculate Θ_S as in Papageorgiou and Chmeralova (2005)[32]. The latter facilitates a translog measure of TFP as in (13) and the estimation of models (5), (7) and (12). Once again, we select two alternative measures for skilled labour, S. For comparison, we take the first to be primary school attainment, PRIM, the measure used by Papageorgiou and Chmeralova (2005). We also adopt their approach to add lnY in the list of regressors to allow for a non-homothetic production function. Panel 1 in Table 6 summarises the panel estimates of (5) and (7). The FGLS and GMM estimates of (5) confirm the key role of valuable skills as an engine of total factor productivity growth. We observe that the coefficient estimates for human capital and diffusion are positive and negative as expected and comparable in size to estimates in Table 4, columns 3-4. Column 3 in the same panel considers non-linear effects in the absorptive capacity of human capital due to research collaboration, model (7). These are similar to results in Table 4 but contrast with those in Table 5 in that the human capital effect on TFP growth is only evident in nations where scientists engage in collaborative research with other scientists in the developed world. This finding suggests that scientists play a catalytic role in the process of innovation and the adoption of new technology.

Panel 2 in Table 6 repeats the estimation exercise using the standardised latent index of human capital, H_S, as described above. Qualitatively, the results here are similar to those in panel 1 but now the human capital effect is much larger when we account for research collaboration using model (7).

[31] 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 primary education, PRIM, infant mortality, MORTAL, and the dummy variables: a Sub-Saharan African country (SSA), a transitional European economy, and a South American economy.

[32] That is, we applied the formula $\Theta_S = (W_S/W_N)S \big/ \left((W_S/W_N)S + N\right)$.

Finally, we utilise the new estimates of Θ_S, (K/Y) and (W_S/W_N) to estimate (12) the results of which appear in Table 7. Here, panel 1 uses PRIM as a measure of skilled labour while panel 2 uses H_S. Feasible GLS estimates in column one suggest that capital and skilled labour are substitutes in conflict with the CSC, hypothesis. Technology, on the other hand, is evidently biased towards skilled labour.

Table 6. Translog Technology, Skills and Diffusion: GMM Panel Estimation

	Benhabib & Spiegel (2005)					
	Panel 1: Primary School			**Panel 2**: Valuable Skills		
Explanatory	**FGLS**	**System GMM**		**FGLS**	**System GMM**	
Variables	**(1A)**	**(1B)**	**(1C)**	**(2A)**	**(2B)**	**(2C)**
Constant	0.018	-0.162*	-0.090	0.012	-0.195*	-0.152
	(0.020)	(0.066)	(0.120)	(0.017)	(0.068)	(0.154)
h	0.014*	0.065*		0.015*	0.070*	
	(0.005)	(0.018)		(0.004)	(0.022)	
h(1-R)			0.035			0.052
			(0.046)			(0.039)
hR			0.065*			0.083*
			(0.027)			(0.021)
h*(A/A^{max})	-0.012*	-0.049*		-0.008*	-0.052*	
	(0.004)	(0.014)		(0.003)	(0.023)	
h*(A/A^{max}) (1-R)			0.016			-0.031
			(0.068)			(0.050)
H*(A/A^{max}) R			-0.061*			-0.078*
			(0.028)			(0.036)
Observations	402	402	402	402	402	402
AB AR(1)		1.71	1.46		3.21	2.61
AB AR(2)		0.33	0.57		1.21	1.18
Hansen: χ^2		16.09	30.31		26.87	26.69

Note**:** In parentheses are standard-errors and * denotes 5% level of significance. *h* denotes years of education and is equal to ln(*H*). More details are in notes to Table 3. Not reported here, Hansen tests of exogeneity of instruments do not reject the null hypothesis in all GMM regressions. All panel regressions include time effects, estimates are available on request. *R* is an indicator variable being equal to one if CoS_t>mean(CoS_t) and equal to zero otherwise.

In order to compare our results with Papageorgiou and Chmeralova (2005), we employ quantile regressions to examine the role of nonlinearities and report results for the lowest and highest quartiles in columns 2-3 in Table 7. Here, the negative coefficient for ln(K/Y) persists but that of ln(W_S/W_N) is now statistically significant for the bottom of the distribution, although the latter is much lower than the estimate reported by Papageorgiou and Chmeralova (2005). The differences may be due to the fact that we control for the role of technology bias or due to differences in empirical methodology in accounting for nonlinearities.

Table 7. Translog Technology, CSC and Skill Bias: Panel & Quantile Estimation

	Papageorgiou-Chmelarova (2003)					
	Panel 1: Primary School			**Panel 2**: Valuable Skills		
Explanatory Variables	**FGLS (1A)**	**Quantile Regressions (1B): q25**	**(1C): q75**	**FGLS (2A)**	**Quantile Regressions (2B) : q25**	**(2C) :**
Constant	0.197*	0.496*	0.467*	-0.502*	-0.647*	-0.305
	(0.085)	(0.206)	(0.253)	(0.051)	(0.148)	(0.159)
ln(K/Y)	-0.043*	-0.058*	-0.052*	0.005	0.037*	0.018
	(0.007)	(0.016)	(0.021)	(0.006)	(0.017)	(0.020)
$\ln(W_S/W_N)$	0.015	0.179*	-0.048	0.593*	0.449*	0.653*
	(0.032)	(0.033)	(0.133)	(0.014)	(0.024)	(0.050)
ln(Y/L)	0.017	-0.029	0.001	0.062*	0.075*	0.045*
	(0.009)	(0.022)	(0.028)	(0.005)	(0.015)	(0.016)
ln(A)	0.136*	0.217*	0.150*	0.119*	0.054*	0.150*
	(0.015)	(0.028)	(0.057)	(0.008)	(0.019)	(0.028)
Observations	458	458	458	458	458	458
Pseudo R^2		0.46	0.41		0.46	0.51

Note**:** In parentheses are standard-errors and * denotes 5% level of significance. *h* denotes years of education and is equal to ln(*H*). More details are in notes to Table 3. All panel regressions include time effects, estimates are available on request. Tests failed to reject the null hypothesis that any of the explanatory variables are weakly exogeneous. Quantile regressions used 500 bootstrap replications. Data for (W_S/W_N) are from Table A.1 in Papageorgiou and Chmeralova (2005). Highlighted estimates are indicate statistically significant differences between the upper quartile (q75) and the lower quartile (q25) in interquantile regressions.

The results in panel 2, Table 7 are in stark contrast to those in panel 1. Using the new estimate of human capital as a basis for skilled labour, S, results in a positive and significant coefficient for ln(K/Y) for the bottom quartile and positive but statistically insignificant for the upper quartile and the average country. Moreover, the coefficient for $\ln(W_S/W_N)$ is also positive and significant. Further, the complementarity between skilled and unskilled labour (SNC) is stronger in more developed economies. Thus, panel 2 is broadly consistent with Papageorgiou and Chmeralova (2005) who find CSC and SNS (i.e., skilled-unskilled substitution) to be more pronounced in developing countries than in developed OECD economies. It also confirms a positive and significant coefficient for ln(Y) as in Papageorgiou and Chmeralova (2005). Last but not least important, is evidence of a skill bias in technical change, given the positive coefficient for ln(A). In contrast to results in panel 1, however, the SBTC effect tends to be more conspicuous in developed countries. These results are in support of CSC, SNC and SBTC and the presence of nonlinear effects whereby CSC and SNS are higher in developing countries while the opposite is true for SBTC. We maintain that the results in panel 2 are more plausible given the comparability of the results with those in Papageorgiou and Chmeralova (2005) and the wider literature.

5. Summary and Conclusion

This paper develops a new index of human capital as a latent unobservable factor identified as *valuable* cognitive skills. It utilises this new measure to consider three alternative models of technology diffusion originating in Nelson and Phelps (1966). The paper also employs the logistic diffusion model of Benhabib and Spiegel (2005) to examine the importance of scientific collaboration as a key determinant of the capacity of nations to absorb foreign technology. The behaviour of the model is further analysed in the context of CES and translog production technologies in order to assess the importance of CSC and SBTC hypotheses in explaining growth patterns.

Overall, the evidence shows that the logistic diffusion model best describes the panel data examined here. Further, the new measure of human capital reveals that long-term income disparities persist in countries that pay little attention to skills. In contrast to previous evidence, we find that the number of countries that are susceptible to poverty traps and stagnation has increased from ten to fifteen over the period 1970-2000. Also, although South America and developed OECD economies have invested heavily on education, they have witnessed minimal progress in valuable skills. At polar ends, Africa and transitional European economies have seen their average skills decline over the period while Asia and South Europe have invested heavily in the quality of education in terms of *valuable* skills. These results call for a major shift in development policy to pay greater attention to skills

Finally, there is strong evidence of skilled-unskilled labour complementarity and a skill bias in new technology, especially in developed countries. However, there is also tentative evidence of capital-skill complementarity. Most importantly, the evidence here indicates that scientific research collaboration is a key determinant of the absorptive capacity of human capital which, in turn, facilitates technology diffusion.

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DATA APPENDIX: Variables, Sources and Countries

Variable	**Definition**	**Source**
Δh	Change in average years of education, h (i.e., growth rate in human capital; within period annual growth).	Barro and Lee (2001) and World Development Indicators.
Δk	Growth of net capital stock per worker/per capita. We follow Benhabib and Spiegel (2005) in computing the initial level of capital stock. Firstly, the initial 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 capital stock for subsequent years are calculates 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.	Penn World Tables (PWT 6.2) and Benhabib and Spiegel (2005).
Δl	Labour growth proxied by population growth.	PWT 6.2.
Δy	Growth of real GDP per worker/per capita relative to the model set-up (The real GDP per capita used is in constant prices: Chain series).	PWT 6.2.
CoS	Per capita scientific journal articles in sciences collaborated with scientists in developed OECD countries.	ISI Web of Knowledge.
$D_{i,t}$	$D_{i,t}$ is the 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's (USA) for the period.	Derived.
h	Average years of schooling in population. 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.	Barro and Lee (2001) and World Development Indicators.
IMMAN	Manufactures imports (% of merchandise imports) (current US$). For Botswana, Sierra Leone and Uganda, we have interpolated the manufactures imports using investment in equipment (%GDP) figure from De Long and Summers (1991); Table XVI column 9. This is also supported by our observation that these countries had large expenditure either for war or military purposes.	World Development Indicators and De Long (1991).
Ke	Per capita capital equipment stock. We assume that all IMMAN are investment in equipments (Ie) and the initial stock is computed as the ratio of (Ie/I)*K where I is total investment and K is the total physical capital stock.	World Development Indicators and De Long (1991).
L	Labour force (Employment).	PWT 6.2.

LPR	Labour force participation rate equal to (L/POP).	Derived.
MORTAL	Infant mortality rates.	UNCTAD Handbook of Statistics.
N	Unskilled labour set equal to (1-PRIM)*POP or equal to (1-H_S)*POP where H_S is new latent index of human capital standardized as [0, 1].	Barro and Lee (2001) and PWT 6.2.
POP	Population.	PWT 6.2.
PRIM	Primary school attainment/100.	Barro and Lee (2001).
R	Indicator variable, equals one if CoS>Mean(CoS) and zero otherwise.	Derived.
S	Skilled labour set equal to PRIM*POP or equal to H_S*POP where H_S is new latent index of human capital standardized as [0, 1].	Barro and Lee (2001) and PWT 6.2.
SciP	Per capita scientific journal article publications in sciences in the country.	ISI Web of Knowledge.
SECO	Average years of secondary school attainment.	Barro and Lee (2001).
TIMSS	Trends in international mathematics and science study (TIMSS): Average Maths and Science scale scores of eighth grade students (Table C2) for years 1995 to 2003. For years 1970 to 1995, we use averages of Maths and Science for students aged 13-14 years in BL for the periods 1970-72; 1982-84; 1988; 1990-91 and spliced at 1995.	International Association for the Evaluation of Educational Achievement (IEA) 1995, 1999, and 2003, and Barro and Lee (2001).
URB	Urban labour force per population at the initial year of the period.	World Development Indicators.
X*m*	Manufacturers exports (% of merchandise exports).	World Development Indicators.
$\mathbf{Y_0}$	Initial real per capita GDP (constant prices: Chain series) for the period.	PWT 6.2.
$Y_0^{\max}$	The leading country's (USA in this case) per capita income.	PWT 6.2.

Countries:
Algeria, Argentina, Australia, Austria, Belgium, Bolivia, Botswana, Brazil, Bulgaria, Cameroon, Canada, Chile, China, Colombia, Congo Dem. Republic (Zaire), Denmark, Egypt, Ethiopia, Finland, France, Germany, Ghana, Greece, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Kenya, Korea, Malawi, Malaysia, Mauritius, Mexico, Morocco, Netherlands, New Zealand, Nigeria, Norway, Pakistan, Paraguay, Peru, Philippines, Poland, Portugal, Romania, Russia, Senegal, Sierra Leone, Singapore, Slovakia, South Africa, Spain, Sri Lanka, Sudan, Sweden, Switzerland, Tanzania, Thailand, Tunisia, turkey, Uganda, UK, Uruguay, USA, Zambia, Zimbabwe.