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Specifying Human Capital: A Review, Some Extensions, and Development Effects

by

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Specifying Human Capital: A Review, Some Extensions, and Development Effects*

Abstract:

A review of the measures of the stock of human capital used in empirical growth research reveals that human capital is mostly poorly proxied. The simple use of the most common proxy, average years of schooling of the working-age population, misspecifies the relationship between education and the stock of human capital. Based on human capital theory, the specification of human capital should be extended to allow for decreasing returns to education and for differences in the quality of a year of education. Cross-country differences in quality-adjusted human capital can account for about half the world-wide dispersion of levels of economic development and for virtually all the development differences across OECD countries.

Keywords: human capital measurement, years of schooling, Mincer specification, educational quality, development accounting

JEL Classification: O4, I2

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1 Introduction

The fundamental question of economic development – why some countries are so rich and others are so poor – has occupied the economics profession ever since it exists. The economists' theoretical account for the proximate causes of cross-country differences in levels of economic development is straightforward: Differences in income levels stem from differences in the amount of factor inputs used in production and from differences in the productivity of the use of these inputs. It is then an empirical question to what extent differences in accumulated inputs or differences in total factor productivity contribute to the international variation of per capita income.

Investing in human capital is one way of accumulating inputs. The acquisition of knowledge and skills is an investment in the sense that people forego consumption for it in order to increase future income. Because workers have invested in themselves to different extents through education, one hour of labor input does not yield the same output across all workers. Education increases future labor productivity and future income and can thus be seen as an investment in human capital, which then is embodied in the human being. This idea can already be found in Adam Smith's (1776/1976, p. 118) classical Inquiry into the Nature and Causes of the Wealth of Nations:

> "A man educated at the expence of much labour and time to any of those employments which require extraordinary dexterity and skill, may be compared to [an] expensive machin[e]. The work which he learns to perform, it must be expected, over and above the usual wages of common labour, will replace to him the whole expence of his education, with at least the ordinary profits of an equally valuable capital."

And in his Principles of Economics, Alfred Marshall (1890/1922, p. 564) stated that

> "The most valuable of all capital is that invested in human beings".

While these citations demonstrate an early awareness of the importance of human capital, it was not before the second half of the twentieth century that economists such as Theodore W. Schultz, Gary S. Becker, and Jacob Mincer developed a thorough theory of human capital.

This paper reviews attempts to derive a measure of the stock of human capital in empirical work and provides some extensions, focusing on education as the central means to accumulate human capital. In his review article of the new empirical evidence in the economics of growth, Temple (1999a, p. 139) points out that "[t]he literature uses somewhat dubious proxies for aggregate human capital." There may be two types of measurement error in the measurement of any variable. Data recording errors constitute a first reason for mismeasurement. But even when the data is perfectly recorded, the measured variable may still be a poor measure of the true variable. This paper focuses on these second measurement errors due to using an imperfect proxy for the true stock of human capital.

The main reason for the use of poor proxies of the stock of human capital is that in most empirical growth studies, the choice of the human capital proxy is hardly reflected upon and depends very much on data availability. Instead of being based on an ad-hoc choice, however, the search for a proxy for the stock of human capital should be led by economic theory. Human capital theory offers a specification of the human capital function which represents the stock of human capital, expressed in money units, as a function of the measured variable of education, expressed in units of time. Therefore, the task of deriving a viable measure of the stock of human capital embodied in the labor force is mainly a task of correctly specifying the form of the relationship between education and human capital. The objective of this paper is to improve on the specification of the human capital measure and to show that there are potentially huge specification errors in the human capital variables used in applied work.

Section 2 reviews the measures of the stock of human capital used in the literature from early growth accounting to the cross-country growth regressions of the mid-1990s. These measures include education-augmented labor input, adult literacy rates, school enrollment ratios, and average years of schooling of the working-age population, which is currently the proxy most commonly employed.

Human capital theory can be used to show that the stock of human capital is misspecified by the simple use of the proxy "average years of schooling" because this includes an incorrect specification of the functional form of the education-human capital relationship (Section 3). Therefore, I present some extensions of the specification of human capital which yield measures which accord to human capital theory. A first extension, proposed by Bils and Klenow (2000), is to account for decreasing returns to investment in education by combining years of education with rates of return to education in a Mincer specification of the function linking education to human capital. Further extensions, based on Gundlach et al. (1998), try to account for cross-country differences in the quality of education, especially through the inclusion of a cognitive-skill index into the human capital function.

With this improved measure of the stock of human capital, the ultimate research question of development effects of human capital can be addressed in a development accounting analysis (Section 4). The results reveal that the differences in the specifications of the human capital variable have a large impact on the share of the international variation in levels of economic development attributed to cross-country differences in accumulated human capital. The misspecification of the human capital function leads to a severe understatement of the development impact of human capital. Quality-adjusted human capital accounts for about half the dispersion in income levels in the world and for nearly the whole income dispersion across OECD countries. This finding corroborates Gary Becker's (1964/1993, p. 12) contention that

> "few if any countries have achieved a sustained period of economic development without having invested substantial amounts in their labor force".

The specification error introduced by the disregard of differences in educational quality is far greater than the recording errors in the data on educational quantity which have been stressed recently in studies by Krueger and Lindahl (2000) and de la Fuente and Doménech (2000). As a theory of the international dispersion of levels of economic development, my results favor a human-capital-augmented neoclassical growth model, where the stock of human capital has *level* effects due to its accumulation as a factor input, over those endogenous growth models where the stock of human capital has *growth* effects because it facilitates technical progress. Section 5 concludes.

2 Human Capital Specification from Early Growth Accounting to Current Cross-Country Growth Regressions

2.1 Education-Augmented Labor Input in Early Growth Accounting

The only factor inputs which were accounted for in the earliest growth accounting studies were physical capital and labor. Thus, the total labor force, which is the linear sum of all workers, was the only measure of input embodied in human beings, implying the assumption that workers are homogeneous. However, Solow (1957, p. 317, fn. 8) was already aware of the importance of skill accumulation as a form of capital formation, conceding in passing that "a lot of what appears as shifts in the production function must represent improvement in the quality of the labor input, and therefore a result of real capital formation of an important kind."

Subsequent growth accounting studies tried to account for the heterogeneity of labor by considering differences in the quality of labor input. Labor input was augmented by considering differences across workers with respect to categories of characteristics, where education was one of several categories including gender, age, and occupational characteristics. In that sense, human capital specification has its predecessors in early growth accounting. Denison (1967) augments labor input to reflect differences in the quality of labor by adjusting total employment for hours worked, age-sex composition, and education. The effect of differences in the gender, age, and educational composition of hours worked upon the average quality of labor is estimated by the use of earnings weights. Assuming that wage differences reflect differences in the marginal product of labor, differences in the wages earned by different labor force groups make it possible to measure differences in their human capital. By using data on the distribution of the labor force across worker categories and weighting each category by its relative average wages, an aggregate labor quality index is constructed which reflects differences in the labor force with respect to the categories, weighted by market returns.

Denison (1967) argues that not the whole wage differential by level of education represents differences which are due to differences in education, because some of the wage differential may represent rewards for intelligence, family background, or credentialism. Therefore, he does not use average wages directly as educational weights, but instead makes the ad-hoc assumption that only three-fifth of the reported wage differentials between the group with eight years of education and each other group represents wage differences due to differences in education as distinguished from other associated characteristics. As education weights, he and many subsequent studies use the ensuing compressed income differentials. Denison (1967) also makes some allowance for differences in days of schooling per year.

Jorgenson and co-authors elaborate on this specification of education-augmented labor input in numerous contributions, many of which are collected in Jorgenson (1995). Especially, they disaggregate the analysis to the level of individual industries and break down the labor input not only by gender, age, and education, but also by such characteristics as employment status and occupational group. This leads to a myriad of labor input categories which are then aggregated on the basis of wage weights to yield a constant quality measure of overall labor input.

The detailed data required for these calculations is only available in a few advanced countries. Since most of the early growth-accounting literature was interested mainly in within-country intertemporal comparisons of indices of the quality of labor, difficulties in cross-country comparisons, stemming mainly from informational deficiencies and measurement differences, were not addressed. Therefore, measures of total labor input adjusted for quality differences, and especially education-augmented labor input, are available only for very few countries.

2.2 Adult Literacy Rates

The availability of national accounts data for a large number of countries and years in the Penn World Table compiled by Summers and Heston (1988, 1991) has initiated a huge literature of cross-country growth regressions, which from the outset considered the inclusion of a measure of human capital. The early contributions to the literature specified the stock of human capital in the labor force by proxies such as adult literacy rates and school enrollment ratios. In most studies, this choice of specification reflects ease of data availability and a broad coverage of countries by the available data (usually coming from UNESCO Statistical Yearbooks) rather than suitability for the theoretical concept at hand. It soon became apparent that specification by these proxies does not yield very satisfactory measures of the stock of human capital available in production.

Studies such as Azariadis and Drazen (1990) and Romer (1990) use the adult literacy rate as a human capital proxy. Literacy is commonly defined as the ability to read and write, with understanding, a simple statement related to one's daily life. The adult literacy rate then measures the number of adult literates (e.g., in the population aged 15 years and over) as a percentage of the population in the corresponding age group:

$$(1) \qquad l = \frac{M_A}{P_A}$$

where l is the adult literacy rate, M_A is the number of literates in the adult population, and P_A is the total adult population.

There has been some discussion about the international comparability of the thus defined variable because it is not easily applied systematically, but adult literacy rates certainly reflect a component of the relevant stock of human capital. However, they miss out most of the investments made in human capital because they only reflect the very first part of these investments. Any educational investment which occurs on top of the acquisition of basic literacy - e.g., the acquisition of numeracy, of logical and analytical reasoning, and of scientific and technical knowledge - is neglected in this measure. Hence using adult literacy rates as a proxy for the stock of human capital implies the assumption that none of these additional investments directly adds to the productivity of the labor force. Therefore, adult literacy rates can only stand for a minor part of the total stock of human capital.[1]

2.3 School Enrollment Ratios

School enrollment ratios, a further human capital proxy used in the literature, measure the number of students enrolled at a grade level relative to the total population of the corresponding age group:

$$e_g = \frac{E_g}{P_g} \tag{2}$$

where e_g is the enrollment ratio in grade level g, E_g is enrollment (the number of students enrolled) at grade level g, and P_g is the total population of the age group that national regulation or custom dictates would be enrolled at grade level g.[2] These enrollment ratios have been used to proxy for human capital in the seminal studies of Barro (1991) and Mankiw et al. (1992)[3] and in the sensitivity study by Levine and Renelt (1992), among many others.

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1 Accordingly, adult illiteracy rates (1-l) have later been used in the construction of school attainment measures to proxy for the percentage of the population without any schooling (see Section 2.4).

2 Gross enrollment ratios take the total number of students enrolled at the grade level as the numerator, while net enrollment ratios take only those students enrolled at the grade level who belong to the corresponding age group P_g.

3 Mankiw et al. (1992) use the proportion of the working-age population enrolled in secondary school as their proxy, obtained by multiplying secondary school enrollment ratios by the fraction of the working-age population which is of school age.

Although some researchers interpret enrollment ratios as proxies for human capital stocks, they may be a poor measure of the stock of human capital available for current production. Enrollment ratios are flow variables, and the children currently enrolled in schools are by definition not yet a part of the labor force, so that the education they are currently acquiring cannot yet be used in production. Current school enrollment ratios do not necessarily have an immediate and stable relationship to the stock of human capital embodied in the current productive labor force of a country. The accumulated stock of human capital depends indirectly on lagged values of school enrollment ratios, where the time lag between schooling and future additions to the human capital stock can be very long and also depends on the ultimate length of the education phase.

Enrollment ratios may thus be seen as - imperfect - proxies of the flow of human capital investment. However, the stock of human capital is changed by the net additions to the labor force, which are determined by the difference between the human capital embodied in the labor force entrants and the human capital embodied in those who retire from the labor force. Therefore, enrollment ratios may only poorly proxy for the relevant flows. First, they do not measure the human capital embodied in the entrants of the labor force this year, but the human capital acquired by current students who might enter the labor force at some time in the future. Second, the education of current students may not at all translate into additions to the human capital stock embodied in the labor force because graduates may not participate in the labor force and because part of current enrollment may be wasted due to grade repetition and dropping out. Third, net investment flows would have to take account of the human capital content of the workers who are retiring from the labor force that year. In sum, enrollment ratios may not even accurately represent changes in the human capital stock, especially during periods of rapid educational and demographic transition (Hanushek and Kimko 2000).[4]

2.4 Levels of Educational Attainment and Average Years of Schooling

Both adult literacy rates and school enrollment ratios seem to have major deficiencies as proxies for the concept of human capital highlighted in theoretical models. Since the

[4] See Pritchett (1996) for an illustration why enrollment ratios can - and in reality seem to - be *negatively* correlated with true accumulation rates of human capital; see also Gemmell (1996) for a critique of the use of enrollment ratios as human capital measures.

inadequacies of these proxies have motivated improvements in the specification of the human capital stock, it cannot be recommended to use either of them as a human capital measure. When looking for a measure of the stock of human capital that is currently used in production, it seems sensible to quantify the accumulated educational investment embodied in the current labor force. Therefore, several studies have tried to construct data on the highest level of educational attainment of workers to quantify the average years of schooling in the labor force. Educational attainment is clearly a stock variable, and it takes into account the total amount of formal education received by the labor force. So average years of schooling have by now become the most popular and most commonly used specification of the stock of human capital in the literature, including studies such as Barro and Sala-i-Martin (1995), Barro (1997, 1999), Benhabib and Spiegel (1994), Gundlach (1995), Islam (1995), Krueger and Lindahl (2000), O'Neill (1995), and Temple (1999b).

Perpetual Inventory Method

Three main methods have been used in the construction of data sets on years of educational attainment in the labor force, each building in one way or another on the data on enrollment ratios discussed previously. The first method to get from school enrollment to average years of schooling, used by Lau et al. (1991) and refined by Nehru et al. (1995), is the perpetual inventory method. If sufficiently long data series on school enrollment ratios are available, the perpetual inventory method (superscript *PIM*) can be used to accumulate the total number of years of schooling S embodied in the labor force at time T by

$$(3) \qquad S^{PIM} = \sum_{t=T-A_h+D_0}^{T-A_l+D_0} \sum_g E_{g,t+g-1}\left(1-r_g-d\right)p_{g,t+g-1}$$

where $E_{g,t}$ is total (gross) enrollment at grade level g at time t as in equation (2), A_h is the highest possible age of a person in the labor force, A_l is the lowest possible age of a person in the labor force, D_0 is the age at which children enter school (typically six), r_g is the ratio of repeaters to enrollments in grade g (assumed to be constant across time), d is the drop-out rate (assumed to be constant across time and grades), and $p_{g,t}$ is the probability of an enrollee at grade g at time t to survive until the year T.[5] By assuming $A_l = 15$ and $A_h = 64$, the studies count all persons between age 15 and 64 inclusive as constituting the labor force. The probability of survival $p_{g,t}$ is calculated on the basis of age-specific mortality rates in each year, which implicitly assumes that the mortality rate is independent of the level of schooling attained. The total number of years of schooling S can then be normalized by the population of working age P_w to obtain the average years of schooling of the working-age population s:

$$(4) \qquad s^{PIM} = \frac{S^{PIM}}{P_w} \ .$$

Much of the data on enrollment rates, repeater rates, age-specific mortality rates, and drop-out rates necessary to implement the calculation on the basis of the perpetual inventory method are not available and have therefore been "statistically manufactured." E.g., enrollment ratios and repeater rates have to be extrapolated backwards, and data gaps have to be closed by interpolations. Both problems are especially severe in the case of tertiary education. Age-specific survival rates have been constructed for a "representative" country in each world region only.

Projection Method

In a second method to get from school enrollment ratios to years of schooling, Kyriacou (1991) builds on information on average years of schooling in the labor force available for the mid-1970s from Psacharopoulos and Arriagada (1986) based on direct census evidence of worker's attainment levels (see below). Data on lagged enrollment ratios are then used to project (superscript *PRO*) average years of schooling in the labor force s for further countries and years T:

$$(5) \qquad s_T^{PRO} = \alpha_0 + \alpha_1 e_{pri,T-15} + \alpha_2 e_{sec,T-5} + \alpha_3 e_{hig,T-5}$$

where $e_{a,t}$ is the enrollment ratio at attainment level a (primary, secondary, and higher) at time t, and the αs are estimated in a regression of the value of the attainment-data based years of schooling in the mid-1970s (i.e., between 1974 and 1977) on prior enrollment rates:

$$(6) \qquad s_{1975}^{ATT} = \alpha_0 + \alpha_1 e_{pri,1960} + \alpha_2 e_{sec,1970} + \alpha_3 e_{hig,1970} + \varepsilon$$

[5] Note that the perpetual inventory formula given in Nehru et al. (1995) is erroneous.

where ε is an error term.

Kyriacou (1991) finds that this relationship is rather strong across the 42 countries in the mid-1970s for which the respective data is available, with an R^2 of 0.82. For the projection, it has to be assumed that the relationship between average years of schooling in the labor force and lagged enrollment ratios is stable over time and across countries.

Attainment Census Method

The third method applied in the construction of attainment data sets is to use direct measures of levels of educational attainment from surveys and censuses. Psacharopoulos and Arriagada (1986) collected information on the educational composition of the labor force from national census publications for six levels of educational attainment *a*: no schooling, incomplete primary, complete primary, incomplete secondary, complete secondary, and higher. Based on these direct data on attainment levels (superscript *ATT*), average years of schooling *s* in the labor force can be calculated as

$$(7) \qquad s^{ATT} = \sum_a \left[n_a \left(\sum_{i=1}^{a} D_i \right) \right]$$

where n_a is the fraction of the labor force for whom attainment level *a* is the highest level attained ($n_a = N_a / L$ with N_a as the number of workers for whom *a* is the highest level attained and *L* as the labor force) and D_a is the duration in years of the *a*th level of schooling.[6] For fractions of the labor force who have achieved an attainment level only incompletely, half the duration of the corresponding level is attributed. The main shortcoming of the data set of Psacharopoulos and Arriagada (1986) is that the year of observation varies greatly across the countries covered, with most of the countries providing only one observation, so that a cross-country analysis is hard to obtain.

Barro and Lee (1993) apply basically the same methodology based on census and survey data on educational attainment levels, but they are able to greatly extent the coverage of countries and years. The greater coverage is partly achieved through a focus on the adult population as a substitute for the labor force (they use $n_a = N_a / P_A$ with P_A

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6 Several studies use years of schooling at the different levels separately (e.g., Barro and Sala-i-Martin 1995, Barro 1997). This seems problematic since, e.g., years of primary schooling can only increase up to universal coverage. The variation across countries with basically universal coverage is mainly caused by cross-country differences in the duration of the primary level D_{pri}, which will depend primarily on an education system's classification of different levels. Therefore, it is not quite clear what, e.g., estimated coefficients in a growth regression really show.

as the total adult population), so that their s^{ATT} represents average years of schooling in the working-age population, i.e. the population aged 25 (or 15) years and over, instead of the actual labor force. Barro and Lee's (1993) attainment levels are based on UNESCO's International Standard Classification of Education (ISCED) and are: no schooling, incomplete first level, complete first level, entered first cycle of second level, entered second cycle of second level, and entered higher level.

Barro and Lee (1993) also use data on adult illiteracy rates - (1-*l*) from equation (1) - to estimate the fraction of the working-age population with no schooling in those instances where direct data from censuses or surveys is not available. Since they observe a high correlation between the no-schooling fraction n_0 and adult illiteracy rates (1-*l*) - 0.95 for the 158 observations where both data are available -, they estimate missing values of the fraction of the working-age population with no schooling n_0 at time T for countries which report both a value for the no-schooling fraction n_0 and a value for adult illiteracy (1-*l*) in another year $T\pm t$ based on

$$n_{0,T} = (1 - l_T)\frac{n_{0,T\pm t}}{(1 - l_{T\pm t})}. \tag{8}$$

When measured at four broad attainment levels (no schooling, first, second, and higher level), 40 percent of all possible data cells (for a total of 129 countries at six points in time) are filled out by available census or survey data, and an additional 16 percent of the cells are filled out by using adult illiteracy rates.

Barro and Lee (1993) go on to estimate the missing observations based on data on school enrollment ratios. They use the perpetual inventory method (see above), starting with the directly observed data points as benchmark stocks and estimating changes from these benchmarks on the basis of school enrollment ratios and data on population by age to estimate survival rates. In Barro and Lee (1993), repeater ratios r and drop-out rates d were neglected in the estimation (see equation (3)), while the revised version of the data set in Barro and Lee (1996) takes account of them. Barro and Lee (2000) additionally account for variations in the duration D_a of schooling levels over time within a country.

De la Fuente and Doménech (2000) point out that there is still a lot of data recording and classification error in the available data sets, giving rise to severe differences in country rankings across data sets and to implausible jumps and breaks in the time-series patterns. They construct a revised version of the Barro and Lee (1996) data set for

OECD countries, relying on direct attainment data and using interpolation and backward projection instead of the perpetual inventory method with enrollment data to fill in missing observations. They collect additional attainment data from national sources, reinterpret some of the data when data points seem unreasonable, and choose the figure which they deem most plausible when different estimates are available. Their treatment of data inconsistencies includes a fair amount of subjective guesswork, so that their heuristic method comes short of a sound scientific methodology. Nevertheless, their revised data set may give a hint to what extent previous data sets are plagued with data recording errors.

Evaluation of the Construction Methods

Before coming to a fundamental critique of the specification of human capital by years of schooling in Section 3.1, some further criticism of the methods used to construct years-of-schooling data sets and of their implementation is warranted. In addition to the limited availability of the data necessary to implement the first method (plain perpetual inventory method), another severe shortcoming is its lack of benchmarking against the available census data on educational attainment. By disregarding the only direct information available on the variable of interest, it is inferior to the third method which combines the perpetual inventory method with census information. The second method (projection method) is based on the assumption that the relationship between average years of schooling in the labor force and lagged enrollment ratios is a stable one. The available data on school attainment in the labor force from censuses and on school enrollment ratios gives ample evidence that this relationship varies over time and across countries, leaving the assumption erroneous and the projections unreliable.

Given these shortcomings of the first two methods, the attainment census method seems to be the most elaborate to date. However, even the Barro and Lee data set has some measurement weaknesses. It represents average years of schooling in the adult population, but not in the labor force. It therefore includes adults who are not labor force participants and it may exclude some of the members of the labor force (Gemmell 1996). The step from reported attainment levels to average years of schooling includes mismeasurement because it is only known whether a person has started and/or completed any given level. For people not completing a level, it is simply assumed that they stayed on for half the years required for the full cycle. For higher education, Barro and Lee (1993) simply assume a duration D_{hig} of four years for all countries. Furthermore, the original censuses and surveys often use varying definitions for the variables collected (Behrman and Rosenzweig 1994).

A direct data recording problem of the Barro and Lee (1993) data set is the poor coverage of the basic data. While 77 of the 129 countries in their data set have three or more census or survey observations since 1945, only nine countries have more than four observations of the 9 potential data points from 1945 to 1985, and only three countries more than five. For any given five-year period since 1960, the number of countries for which census or survey data is available ranges from a minimum of 14 countries (in the period surrounding 1985) to a maximum of 78 (1980) out of the 129 countries in the data set. To give an example from the de la Fuente and Doménech (2000) data set, only 40 of the 147 observations (21 countries times 7 points in time) on secondary attainment in the data set - or 27 percent - are original observations taken directly from censuses or surveys, while the rest is interpolated in one way or the other. It would be reasonable to conclude that such a coverage does not provide a sensible basis for panel estimation. Accordingly, Krueger and Lindahl (2000) substantiate severe data measurement errors in panel data on average years of schooling. Hence, de la Fuente and Doménech's (2000, p. 12) conclusion is correct that "a fair amount of detailed work remains to be done before we can say with some confidence that we have a reliable and detailed picture of worldwide educational achievement levels or their evolution over time." By contrast, basically all observations in the OECD sample for 1990 are direct census or survey observations, allowing for a reasonable data quality at least for this sample at this specific point in time.

3 Human Capital Specification: A Critique and Two Extensions

3.1 Critique of Schooling Years as a Specification of Human Capital

Apart from the problems of *recording* average years of schooling in the labor force, there are more fundamental problems with the *specification* of the stock of human capital by average years of schooling (cf. Mulligan and Sala-i-Martin 2000). Although it is the most commonly employed measure, using the unweighted sum of schooling years linearly as a measure of the stock of human capital lacks a sound theoretical foundation. There are two major criticisms which render years of schooling a poor proxy for the human capital stock. First, one year of schooling does not raise the human capital stock by an equal amount regardless of whether it is a person's first or seventeenth year of schooling. Second, one year of schooling does not raise the human capital stock by an equal amount regardless of the quality of the education system in which it has taken place.[7]

As for the first point, specifying human capital by average years of schooling implicitly gives the same weight to any year of schooling acquired by a person. I.e., productivity differentials among workers are assumed to be proportional to their years of schooling. This disregards the findings of a whole microeconometric literature on wage rate differentials which shows that there are decreasing returns to schooling (Psacharopoulos 1994). Therefore, a year of schooling should be weighted differently depending on how many years of schooling the person has already accumulated.

As for the second point, using years of schooling as a human capital measure gives the same weight to a year of schooling in any schooling system at any time. I.e., it is assumed to deliver the same increase in skills regardless of the efficiency of the education system, of the quality of teaching, of the educational infrastructure, or of the curriculum. In cross-country work, a year of schooling in, say, Papua New Guinea is assumed to create the same increase in productive human capital as a year of schooling in, say, Japan. Instead, a year of schooling should be weighted differently depending on the quality of the education system in which it has taken place. In the following two sub-sections, I propose specifications of the human capital stock which deal with these two criticisms.

3.2 The Mincer Specification and Decreasing Returns to Education

The stock of human capital embodied in the labor force is a variable expressed in money units. To transform a measure of education measured in units of time into the stock of human capital expressed in units of money, each year of schooling should be weighted

[7] Additionally, using average years of schooling assumes perfect substitutability of workers across attainment levels and a constant elasticity of substitution across sub-groups of workers at any time and place (Mulligan and Sala-i-Martin 2000).

by the earnings return it generates in the labor market. Human capital theory offers a straightforward specification of the functional form of this relationship between education and the stock of human capital, the human capital earnings function (Mincer 1974, cf. Chiswick 1998). Assuming that the total cost C to an individual of investing into a year of schooling lies in the earnings which he or she foregoes during that year, annual earnings W after t years of schooling are equal to annual earnings with $t-1$ years of schooling plus the cost of the investment ($C_t = W_{t-1}$) times the rate of return r on that investment:

(9)' $$W_t = W_{t-1} + r_t W_{t-1} \ .$$

By mathematical induction, it follows that earnings after s years of schooling are given by:

(9)" $$W_s = W_0 \prod_{t=1}^{s} \left(1 + r_t\right) \ .$$

Taking natural logarithms and applying the approximation that, for small values of r, $\ln(1+r) \approx r$, yields

(9)"' $$\ln W_s = \ln W_0 + \sum_{t=1}^{s} r_t \ .$$

For $r = r_t$ being constant across levels of schooling, this is equal to

(9) $$\ln W_s = \ln W_0 + rs \ .$$

Thereby, the relationship in equation (9)' between earnings and investments in education measured in money units is converted to the relationship in equation (9) between the natural logarithm of earnings and investments in education measured in time units. That is, the logarithm of individuals' earnings is a linear function of their years of schooling. This log-linear formulation suggests that each additional year of schooling raises earnings by r percent.

Mincer (1974) estimated the rate of return to education r for a cross-section of workers as the regression coefficient on years of schooling in an earnings function like (9), controlling for work experience of the individuals. A whole literature of micro labor studies has confirmed that this log-linear specification gives the best fit to the data (cf. Card 1999, Krueger and Lindahl 2000). To be able to interpret the schooling coefficient in an earnings function as the rate of return to education, however, the assumption must hold that total costs of investment in the *t*th year of schooling C_t are equal to foregone earnings W_{t-1}. If the opportunity cost of schooling is a full year's earnings, this would imply that there are no direct costs such as tuition, school fees, books, and other school supplies. Furthermore, the regression coefficient in the earnings function method is a biased measure of the rate of return if age-earnings profiles are not constant for different levels of education.

Therefore, rates of return estimated by the elaborate discounting method, which can account both for the total cost of schooling and for variable age-earnings profiles, are superior to estimates based on the earnings function method. The elaborate discounting method consists in calculating the discount rate r which equates the stream of costs of education to the stream of benefits from education:

$$(10) \qquad \sum_{t=1}^{s}\left(C_{h,t}+W_{l,t}\right)(1+r)^{t}=\sum_{t=s+1}^{A_h}\left(W_{h,t}-W_{l,t}\right)(1+r)^{-t}$$

where C_h is the resource cost of schooling incurred to achieve a higher level h from a lower level l, W_l are the foregone earnings of the student while studying, (W_h – W_l) is the earnings differential between a person with a higher level of education and a person with a lower level of education, s is years of schooling, and A_h is the highest possible working age.

By counting both private and public educational expenditures as the cost of schooling C, the elaborate discounting method is able to estimate social rates of return to education. Social - as opposed to private - rates of return are the relevant choice when dealing with questions from a society's point of view. The estimated rates of return are "narrow-social," taking account of the full cost of education to the society (including public expenditure) while disregarding any potential external benefits. Recent studies by Heckman and Klenow (1997), Acemoglu and Angrist (2000), and Ciccone and Peri (2000) show that there is little evidence in favor of such external returns to education.[8]

As first suggested by Bils and Klenow (2000), the micro evidence derived from the log-linear Mincer formulation can be used to specify the aggregate human capital stock in macro studies as

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[8] Note that if there were signalling effects in the private rate of return, the social rate of return might be overstated (cf. Weiss 1995). See Temple (2000) for a discussion of the issues involved.

(11) $H^M = e^{\phi(s)}L \quad \Leftrightarrow \quad h^M = e^{\phi(s)}$

where H^M is the stock of human capital based on the Mincer specification, L is labor as measured by the number of workers,[9] and $h \equiv H/L$ is the stock of human capital per worker. The function $\phi(s)$ reflects the efficiency of a unit of labor with s years of schooling relative to one with no schooling. With $\phi(s) = 0$, the specification melts down to one with undifferentiated labor as in the earliest growth-accounting studies (Section 2.1). Furthermore, the derivative of this function should equal the rate of return to education as estimated in the labor literature, so that $\phi'(s) = r$. In the simplest specification, this would imply

(12) $\phi(s) = rs$.

Thereby, a human capital measure can be constructed for every country by combining data on years of schooling with rates of return estimated in micro labor studies which weight each year of schooling by its market return.[10] This approach of specifying human capital stocks based on the Mincer regression has already been used in several studies, including Bils and Klenow (2000), Klenow and Rodríguez-Clare (1997b), Hall and Jones (1999), and Jovanovic and Rob (1999).[11] Note that this approach is similar to weighting worker categories by relative wage rates as applied by the growth-accounting literature in the construction of education-augmented labor input (see Section 2.1).

In addition to taking account of the log-linear relationship between earnings and schooling, this specification can also be used to include decreasing returns to education. While the original work by Mincer entered schooling linearly over the whole range of schooling years, international evidence as collected by Psacharopoulos (1994) suggests that rates of returns to education are decreasing with the acquisition of additional

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[9] Note that in this work, no adjustment is made for differences in hours worked, as the early growth accounting studies did (Section 2.1).

[10] In addition to rates of return to each year of education, Bils and Klenow (2000) introduce an influence of teachers' education, measured by the stock of human capital 25 years earlier, into their measure of human capital. However, it is not clear why teachers' education should have an influence on the level of human capital apart from the one reflected in the returns to education. They also include a wage effect of experience, measured by age less years of schooling less 6, whereas the current paper focuses on the human capital accumulated through education.

[11] Topel (1999) and Krueger and Lindahl (2000) also specify the relationship between income and years of schooling in a log-linear way.

schooling. Therefore, one year of schooling should be weighted differently depending on whether it is undertaken by a student in primary school, in high school, or in college. The available evidence allows a piecewise linear specification for the primary, secondary, and higher level of schooling:

$$(13) \qquad \phi(s) = \sum_a r_a s_a \quad \Rightarrow \quad H_i^M = e^{\sum_a r_a s_{ai}} L_i \quad \Leftrightarrow \quad h_i^M = e^{\sum_a r_a s_{ai}}$$

where r_a is the rate of return to education at level a and s_{ai} is years of schooling at level a in country i.[12]

Barro and Lee (2000) argue that there are potential problems with the available estimates of returns to education because of biases through unmeasured characteristics like ability and because of disregard of social benefits. However, ample research in the modern labor literature has shown that the upward ability bias is offset by a downward bias of about the same order of magnitude due to measurement error in years of education (cf. Card 1999). Estimates based on siblings or twin data and instrumental variable estimates based on family background or institutional features of the school system are of about the same magnitude as rates of return to education estimated by cross-sectional regressions of earnings on schooling, suggesting that rates of return to education reflect real productivity enhancements. Furthermore, recent studies have found no evidence in favor of externalities to education (see above).[13]

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12 Bils and Klenow (2000) suggest decreasing returns to schooling of the form $\phi(s) = \frac{\alpha}{1-\beta} s^{1-\beta}$, $\beta > 0$, which in applied terms becomes broadly equivalent to equation (13).

13 Mulligan and Sala-i-Martin (1997) also suggest a measure of human capital based on labor income, namely the ratio of the average wage of the labor force to the wage of a person without any schooling. This wage of a person with zero years of schooling is measured as the exponential of the constant term α_0 from a Mincer regression like equation (9). This method weights different segments of the labor force by the income at different levels of education. While Mulligan and Sala-i-Martin (1997) calculate stocks of human capital for the states of the United States, the lack of the detailed labor-income data necessary to pursue this method in most countries of the world will make it impossible to apply such measures in cross-country research in the near future. In any event, for the calculation of the aggregate stock of human capital, this approach should yield estimates equivalent to using estimated rates of return to education in equation (13). Mulligan and Sala-i-Martin (2000) further expand on the idea of aggregating heterogeneous workers into a stock of human capital based on their educational attainment, yielding optimal index numbers for human capital stocks which minimize an expected-error function.

3.3 The Quality of Education

While several studies have by now taken on the Mincer specification to deal with the first criticism, the second criticism of qualitative differences in a year of schooling has as yet not led to a generally accepted refinement in human capital measurement. However, it is not just the *quantity* of education, i.e. the average years of schooling s embodied in the labor force, which differs across countries, but also the *quality* of each year of schooling, i.e. the cognitive skills learned during each of these years. One year of schooling is not the same everywhere because one unit of s may reflect different amounts of acquired knowledge in different countries. Estimated development effects of human capital based on merely quantitative measures may be strongly misleading if qualitative differences do not vary with years of education. Therefore, differences in the quality of education should be introduced into the human capital measure in addition to differences in the mere quantity of education to account for how much students have learned in each year. In what follows, three suggestions are made as to how to adjust the specification of the human capital function for quality differences.

Educational Inputs

The first attempt to account for differences in educational quality is to use proxies for the quality of educational inputs. These measures of the amount of inputs used per student in the education system are then entered as separate explanatory variables in growth regression analyses, presumably reflecting an additional effect of human capital. Barro (1991) already added student-teacher ratios to his analysis as a crude proxy for the quality of schooling, Barro and Sala-i-Martin (1995) use the ratio of government spending on education to GDP, and Barro and Lee (1996) collect data on educational expenditure per student, student-teacher ratios, teacher salaries, and length of the school year to proxy for the quality of educational inputs.

However, it has repeatedly been shown that such measures of educational inputs are not strongly and consistently linked to acquired cognitive skills, rendering them a poor proxy for educational quality (Hanushek 1996). The input measures disregard the huge differences in the effectiveness with which inputs are put to use in different schooling systems, caused mainly by differences in institutional features of the education systems such as centralization of examinations or extent of school autonomy (Wößmann 2000).

Country-Specific Rates of Return to Education

Because of the lack of a systematic relationship between resource inputs and educational quality, a second specification to account for qualitative differences in a year of schooling can be thought of building on country-specific rates of return to education. Under the assumptions that global labor markets are perfectly competitive, that labor is perfectly mobile internationally, and that employers are perfectly informed about the human capital quality of workers, differences in the quality of education of the work force would be captured by differences in the rates of return to education. Therefore, country-specific rates of return may already reflect differences in the quality of education across countries. A quality-adjusted measure of the human capital stock could then be specified as

(14) $$h_i^r = e^{\sum_a r_{ai} s_{ai}}$$

where h_i^r is the stock of human capital per worker (based on country-specific measures of r) in country i, r_{ai} is the rate of return to education at level a in country i, and s_{ai} is average years of schooling at level a in country i.

Unfortunately, the data which are available on country-specific rates of return to education seem to be plagued with a high degree of measurement error and may presumably contain more noise than information. The figures collected by Psacharopoulos (1994) show a degree of variation which is difficult to interpret in terms of differences in schooling quality (see Section 3.4). Furthermore, the three assumptions mentioned which underlie the hypothesis that country-specific rates of return to education capture cross-country differences in the quality of human capital are undoubtedly wrong. Labor markets are not very competitive in many countries, given collective bargaining mechanisms and uniform wage setting. Labor is highly immobile across countries, and employers are not perfectly informed about the acquired skills of potential employees. Consequently, qualitative differences in education are probably not well captured by the available data on country-specific rates of return to education.

Direct Tests of Cognitive Skills

Neither educational input measures nor country-specific rates of return appear to give good proxies for accumulated cognitive skills. Therefore, the most promising way to introduce an adjustment for differences in the quality of education builds on direct measures of the cognitive skills of individuals obtained from tests of cognitive achievement (Gundlach et al. 1998). There are two international organizations which have conducted a series of standardized international tests in varying sets of countries to assess student achievement in the fields of mathematics and natural sciences. The International Assessment of Educational Progress (IAEP), which builds on the procedures developed for the main national testing instrument in the United States, administered two international studies in 1988 and 1991, both encompassing mathematics and science tests. The International Association for the Evaluation of Educational Achievement (IEA), an agency specializing in comparative education research since its establishment in 1959, conducted cross-country mathematics studies in 1964 and 1981, cross-country science studies in 1971 and 1984, and the Third International Mathematics and Science Study (TIMSS) in 1995. Most studies include separate tests for students in different age groups (primary, middle, and final school years) and in several subfields of the subjects.

Hanushek and Kimko (2000) combine all of the available information on mathematics and science scores up to 1991 to construct a single measure of educational quality for each country. All together, they use 26 separate test score series (from different age groups, subfields, and years), administered at six points in time between 1965 and 1991, and encompassing a total of 39 countries which have participated in an international achievement test at least once. To splice these test results together for each country, they first transform all test scores into a "percent correct" format. To account for the different mean percent correct of the test score series, their quality index $QL2*$ makes use of intertemporally comparable time series information on student performance in the United States provided by the National Assessment of Educational Progress (NAEP). These national tests establish an absolute benchmark of performance to which the US scores on international tests can be keyed. Thus, the results of the different test series are combined by allowing the mean of each international test series to drift in accordance with the US NAEP score drift and the US performance on each international comparison. The constructed quality measure is a weighted average of all available transformed test scores for each country, where the weights are the normalized inverse of the country-specific standard error of each test, presuming that a high standard error conveys less accurate information. By combining tests from the relevant time range when current workers were students, the measure tries to approximate the cognitive skills embodied in the current labor force.[14]

To incorporate the thus measured cross-country differences in educational quality into measures of the stock of human capital, I normalize Hanushek and Kimko's (2000) educational quality index for each country relative to the measure for the United States. This measure of relative quality can then be viewed as a quality weight by which each year of schooling in a country can be weighted, where the weight for the United States is unity. To obtain a quality-adjusted human capital specification, the quality and quantity measures of education are combined with world-average rates of return to education at the different education levels in a Mincer-type specification of the human capital function:

$$h_i^Q = e^{\sum_a r_a Q_i s_{ai}} \tag{15}$$

where r_a is the world-average rate of return to education at level a and Q_i is Hanushek and Kimko's (2000) educational quality index for country i relative to the US value.

One virtue of this quality adjustment of the human capital specification is that one may think of the quality of human capital to rise continually and without an upper bound. By contrast, the growth in pure quantity specifications of human capital is bounded because educational attainment is asymptotically a constant. Such a specification is hard to reconcile with most models of economic growth, where the stock of physical capital also has no natural upper bound. A further virtue of the final specifications of h_i^r and h_i^Q is that they yield one single human capital variable. Since human capital is embodied in the labor force, it is more natural to think of it as one combined factor of production, rather than as several independent factors. By combining information on the labor force, quantity of education, rates of return to these educational investments, and quality of this education, the final quality-adjusted human capital specification is more readily interpreted in growth and development applications.

[14] Hanushek and Kimko (2000) show that such quality measures of education matters more in growth regressions than quantity measures, a finding also confirmed by Barro (1999).

3.4 Comparison of the Different Specifications

Human Capital Data

To be able to compare the different measures of human capital proposed in the literature, Table A1 in the Appendix presents estimates of human capital stocks for the different specifications for 1990 or the most recent year available. To facilitate comparisons of the different specifications, values are reported relative to the United States, while the first row in each column shows the absolute US value. Countries are ranked according to output per worker.

Adult literacy rates l and school enrollment ratios e are taken from the UNESCO (2000) World Education Indicators. Adult literacy rates l refer to the population aged 15 years and over and are for both sexes in 1990. School enrollment ratios e are gross enrollment ratios in primary, secondary, and tertiary education for both sexes in 1990. e^{MRW} refers to the indicator used by Mankiw et al. (1992), which is the average percentage of the working-age population enrolled in secondary school for 1960-1985.

Average years of schooling calculated by the perpetual inventory method s^{PIM} are for total (primary, secondary, and tertiary) education in 1987 as calculated by Nehru et al. (1995). s^{PRO} are Kyriacou's (1991) projected average years of schooling for 1985, as reported in Benhabib and Spiegel (1994). Average years of schooling based on the attainment census method s^{ATT} are taken from Barro and Lee (2000) and refer to years of total (primary, secondary, and higher) education in the total population aged 15 and over in 1990. s^{DD} is the revision of Barro and Lee's average years of schooling in 1990 for OECD countries by de la Fuente and Doménech (2000).

In calculating the human capital specifications of Sections 3.2 and 3.3, I use average years of schooling s_a^{ATT} separately at the primary, secondary, and higher level for 1990 from Barro and Lee (2000). Years of schooling in the population aged 15 and over are taken because this age group corresponds better to the labor force for most developing countries than the population aged 25 and over. The rates of return to education r_a used in h^M and h^Q are world-average social rates of return at the primary, secondary, and higher level of education estimated by the elaborate discounting method. As reported by Psacharopoulos (1994, Table 2), the world-average social rate of return to education is

20.0 percent at the primary level, 13.5 percent at the secondary level, and 10.7 percent at the higher level.

Instead of using equation (13) as the function $\phi(s)$ which links the stock of human capital to average years of schooling in equation (11), Hall and Jones (1999) and Gundlach et al. (1998) use

$$(16) \qquad \phi^{HJ}(s) = \begin{cases} r^{Pri} s & \text{if } s \le D_{pri} \\ r^{Pri} D_{pri} + r^{Sec}\left(s - D_{pri}\right) & \text{if } D_{pri} < s \le D_{pri} + D_{\sec} \\ r^{Pri} D_{pri} + r^{Sec} D_{\sec} + r^{High}\left(s - D_{pri} - D_{\sec}\right) & \text{if } s > D_{pri} + D_{\sec} \end{cases} \Rightarrow h^{HJ} = e^{\phi^{HJ}(s)}.$$

Hall and Jones (1999) additionally assume that $D_{pri} = D_{sec} = 4$ for each country. This equation yields a biased allocation of level-specific rates of return to respective schooling years. For example, all the schooling years in a country whose average years of schooling are less than 4 will be weighted by the rate of return to primary education, although presumably some of the years which make up the total stock will have been in secondary or higher education. By just looking at the average and not splitting down the acquired years of education into those acquired at the primary, secondary, and higher levels, this method allocates the wrong rates of return to a substantial part of the acquired schooling years. Furthermore, Hall and Jones (1999) employ private rates of return to education calculated on the basis of the earnings function method, also reported in Psacharopoulos (1994), using the ad-hoc assumption that the rate of return to primary education equals the average rate of return in Sub-Saharan Africa (13.4 percent), the rate of return to secondary education equals the world-average rate of return (10.1 percent), and the rate of return to higher education equals the average rate of return in OECD countries (6.8 percent).[15] To be able to compare my estimates of h^M, h^r, and h^Q to the method used by Hall and Jones (1999), I also report their measure as h^{HJ}, updated to 1990 with years of schooling from Barro and Lee (2000).

In calculating h^r, country-specific social rates of return to education at the three levels estimated by the elaborate discounting method - on which the world-average rates used in h^M and h^Q are based - are taken. However, the country-specific rates of return reported by Psacharopoulos (1994) include an implausible range of values, with rates of

[15] Note that while in general, narrow-social rates of return must be lower than private rates, the reported private estimates based on the earnings function method are even lower than the narrow-social estimates based on the elaborate discounting method.

return to primary education ranging from 2 percent in Yemen to 66 percent in Uganda. Yemen's low figure makes it the country with the lowest h^r in the sample, while Uganda's and Botswana's high figures make them the countries with the highest h^r. Morocco's high figure stems from a reported rate of return to primary education of 50.5 percent, which compares to a regional average of 15.5 percent and an income-group average of 18.2 percent. These implausible results make a sensible use of country-specific rates of return virtually impossible.

As the quality measure Q for the quality-adjusted human capital specification h^Q, I use Hanushek and Kimko's (2000) index of educational quality $QL2*$, relative to the US value. To obtain a full set of human capital estimates, some values for s and Q (and for r in h^r) have been imputed. The imputation takes the mean of the respective regional average and the respective income-group average for any country with a missing value on one of these variables, using the World Bank's (1992) classification of countries by major regions and income groups.[16]

Comparison

The human capital estimates in Table A1 show that the different specifications can yield very different measures of the human capital stock of a country. Even among the different estimation methods of average years of schooling s, large differences exist. E.g., while Mauritania's s^{ATT} is 2.42 years and Switzerland's s^{ATT} is 10.14 years, their s^{PIM} is about the same (6.66 and 6.96 years). Likewise, Spain's s^{PRO} of 9.70 years is 3.26 years higher than its s^{ATT} of 6.44 years, while Taiwan's s^{PRO} of 4.67 years is 3.31 years lower than its s^{ATT} of 7.98 years. Even between the two measures based on the attainment census method (s^{ATT} and s^{DD}), France shows a difference of 3.92 years.

To allow for an overall comparison of the different specifications, Table 1 reports correlation coefficients among the 11 human capital measures. Because the data sets cover different samples of countries, the number of countries covered jointly by each pair of measures is reported in brackets below the correlation coefficients. For example, there is no country jointly covered by the l and s^{DD} data sets, because the UNESCO does not report adult literacy rates l for advanced countries and de la Fuente and Doménech's

16 The regions used are Asia, Latin America, Sub-Saharan Africa, North Africa, Middle East, Eastern Europe, and OECD. The income groups are low, lower-middle, upper-middle, and high income.

(2000) data set s^{DD} is available only for OECD countries. The correlation between the enrollment ratio e and the three broad-sample schooling years variables s^{PIM}, s^{PRO}, and s^{ATT} is fairly high (between 0.83 and 0.90), suggesting that enrollment ratios may not be an altogether bad proxy for the quantity of schooling after all. The correlations among the three broad-sample schooling-years variables s range from 0.88 to 0.90, showing a comparable broad-sample distributions. When compared to the revised OECD sample data set s^{DD}, however, the correlation is very low (0.35, 0.47, and 0.79, respectively). Both s^{DD} and h^{r} in general show a low correlation to all other human capital specifications. Barro and Lee's (2000) s^{ATT} and the Mincer specification h^{M} are highly correlated (0.97), as are the two measures based on the Mincer specification, h^{M} and h^{HJ} (0.98). The correlation between the quality-adjusted human capital specification h^{Q} and most other specifications is relatively low.

4 Human Capital and Economic Development

4.1 Two Theoretical Views on Human Capital and Economic Development

The ultimate aim of specifying the stock of human capital was to assess its relevance for cross-country differences in the levels of economic development. Research on economic growth in general deals with three related but conceptually distinct central issues: world growth, country growth, and dispersion in income levels (Klenow and Rodríguez-Clare 1997a). Research on the first issue tries to explain the continuous growth of income per capita in the world economy, research on the second issue deals with cross-country differences in growth rates, and research on the third issue tries to answer why some countries are significantly richer than others at a given point in time. In this paper, I deal with the third issue - explaining levels rather than explaining growth -, which is called "development accounting" by King and Levine (1994) because it looks for sources of differences in economic development across the countries in the world. The focus on dispersion in levels of development is chosen because they are arguably the ultimate reason why research is interested in economic growth in the first place. Differences in development levels capture differences in long-run economic performance which are directly relevant to welfare, while recent studies show that differences in growth rates are largely transitory (cf. Hall and Jones 1999).

Human capital takes a central role in most theories of economic growth and development. Both the augmented neoclassical growth model and most endogenous growth models stress the importance of human capital for development in one way or another. However, the different models can be summarized into two distinct groups of theoretical views on the relationship between human capital and economic development (cf. Aghion and Howitt 1998, Benhabib and Spiegel 1994). In the first view, the accumulation of human capital as a factor of production drives economic growth, so that differences in levels of human capital are related to differences in output *levels* across countries (the "neoclassical view"). In the second view, a greater human capital stock affects economic growth mainly by facilitating innovation and adoption of new technologies, so that differences in levels of human capital cause differences in output *growth* across countries (the "technical-progress view").

The "Neoclassical View"

The first view - that growth rates of human capital should be connected to growth rates of income - can be easily depicted on the basis of the human-capital-augmented neoclassical growth model, where human capital enters as a factor of production.[17] In his neoclassical growth model, Solow (1956) uses a macroeconomic Cobb-Douglas production function with labor as an homogeneous factor and with physical capital as the only factor of production which can be accumulated. Mankiw et al. (1992) augment this model by introducing human capital as an additional factor of production which can be accumulated, acknowledging that labor is not an homogeneous factor. The level of output Y produced in a country i is then given by

$$(17) \qquad Y_i = K_i^{\alpha}\left(h_i L_i\right)^{1-\alpha} A_i^{1-\alpha}$$

where K_i is the stock of physical capital in country i, α is the production elasticity of physical capital, and A_i is the level of total factor productivity in country i. Steady-state output per worker $y_i \equiv Y_i / L_i$ is then given as

$$(18) \qquad y_i = k_i^{\alpha} h_i^{1-\alpha} A_i^{1-\alpha} \qquad \Leftrightarrow \qquad y_i = \left(\frac{k_i}{y_i}\right)^{\frac{\alpha}{1-\alpha}} h_i A_i$$

[17] Endogenous growth models in the spirit of Lucas (1988), which also view human capital as an input factor in the production function, share the same result.

where $k_i \equiv K_i / L_i$ is the ratio of physical capital to labor. Thus, the steady-state *level* of output is a function of the *level* of human capital.

Long-run growth in this model is unaffected by the accumulation of human capital inputs because the marginal product of each input is diminishing. However, accumulation of human capital leads to output growth along a transitional growth path from one steady-state to the next. Equation (18) implies that the growth rate of output $\gamma_{y_i} \equiv \Delta y_i / y_i$ is given as

(19) $$\gamma_{y_i} = \alpha\gamma_{k_i} + (1-\alpha)\gamma_{h_i} + (1-\alpha)\gamma_{A_i} \ .$$

Thus, in the "neoclassical view," differences in growth rates across countries are related to differences in the rates at which human capital is accumulated.

The "Technical-Progress View"

The second view - of effects of human capital levels on economic growth - is the central part of many endogenous growth models, and it goes at least as far back as Nelson and Phelps (1966). In this "technical-progress view," the growth of total factor productivity depends on the stock of human capital. This may be either due to effects of human capital on the domestic production of technological innovation (Romer 1990) or due to effects of human capital on the adoption and implementation of new technology from abroad (Nelson and Phelps 1966). In either case, the growth of total factor productivity *A* in country *i* is a positive function of the country's average level of human capital *h*:

(20) $$\gamma_{A_i} = \psi(h_i), \quad \psi'(h_i) > 0 \ .$$

This relationship implies that output *growth* is a function not only of the growth of human capital but also of the *level* of human capital.

Knowledge Advances and Cross-Country Income Distribution

This second class of models emphasizes the endogenous nature of growth and technical progress. In that sense, the main contribution of these endogenous growth models is to give an explanation of economic growth over time, usually by suggesting microfoundations for technological advances. As noted above, this issue is conceptually distinct from the development accounting question raised in this paper. Specifically, technological differences across countries should be transitory since technological knowledge is fairly free to move across countries as long as a country is open to the adoption of technological advances from abroad. As is directly evident from the Nelson and Phelps (1966) model of technological catch-up, the effect of the human capital stock on the growth of total factor productivity is a short-run effect of catching up to the technological leader. In the long run, total factor productivity in any country grows again at the growth rate of the world technological frontier, which in that model is exogenous. And while the innovation models endogenize the growth rate of the world technological frontier, this will not have an effect of the long-run income distribution across countries as long as catching-up through technological diffusion is taking place.

One of the central ideas of the innovation models is actually that technological knowledge is a non-rival and non-excludable good. Therefore, by the very nature of technological knowledge, all countries should in principle have access to the same technologies, and even at a relatively modest cost (Olson 1996). The only way in which the knowledge available for productive use may differ across countries is through the knowledge embodied in people, i.e. through the available stock of human capital. Topel (1999) suggests that in that sense, the differences between the two views may be more semantic than real because human capital, when defined broadly, may encompass the creation of knowledge in a person and the ability of human beings to apply new knowledge. The non-rivalry and non-excludability of technological knowledge implies that the "technical-progress view," while providing a possible explanation of worldwide advances in knowledge, should not be a major factor in cross-country differences in development levels.

In contrast, the "neoclassical view" takes worldwide technical progress as given and provides an explanation of economic development - the accumulated stocks of factor inputs - which may very well differ across countries.[18] Therefore, I use the neoclassical growth specification of equation (18) to account for the relative contributions to the cross-country dispersion of levels of economic development by the stock of human capital, the stock of physical capital, and the level of total factor productivity.

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[18] Since neoclassical and endogenous growth models are thus able to answer distinct research questions, they should be viewed as complements (cf. Mankiw 1995).

4.2 World-Wide Development Accounting Results

Methodology and National Accounts Data

Since the empirical interest is in the contribution of differences in human capital stocks to cross-country differences in levels of economic development, I use the "covariance measure" proposed by Klenow and Rodríguez-Clare (1997b) to decompose the international variance in output per worker (the measure of the level of economic development) into the relative contributions of differences in human capital stocks, in physical capital stocks, and in levels of total factor productivity. From equation (18), one can derive

(21)'
$$\begin{aligned}\operatorname{var}(\ln(y)) &= \operatorname{cov}(\ln(y),\ln(y)) \\ &= \operatorname{cov}(\ln(y),\ln(h)) + \operatorname{cov}\left(\ln(y),\ln\left((k/y)^{\frac{\alpha}{1-\alpha}}\right)\right) + \operatorname{cov}(\ln(y),\ln(A))\end{aligned}$$

This decomposition allows the measurement of the relative contributions of the three factors as percentages:

(21)
$$\frac{\operatorname{cov}(\ln(y),\ln(h))}{\operatorname{var}(\ln(y))} + \frac{\operatorname{cov}\left(\ln(y),\ln\left((k/y)^{\frac{\alpha}{1-\alpha}}\right)\right)}{\operatorname{var}(\ln(y))} + \frac{\operatorname{cov}(\ln(y),\ln(A))}{\operatorname{var}(\ln(y))} = 1\,.$$

The three terms on the left hand side equal the coefficients from regressing ln(y) on the logs of each of the three factors separately. Applying this method gives the respective average fraction of output dispersion across countries that can be statistically attributed to international differences in human capital stocks and in phyical capital-output ratios, leaving the rest to be explained by residual total factor productivity. Precisely, the three terms can be interpreted as the percentage of one percent which the respective input in a given country can be expected to be above the mean across countries, conditional on output per worker in that country being one percent above the mean across countries.

As a robustness test for the results of the covariance measure, the "five-country measure," which is based on a calculation in Hall and Jones (1999), focuses on the highest and lowest part of the sample distribution. It shows, also in percentage terms, how much of the difference in output per worker between the five most developed and the five least developed countries (in terms of output per worker) is due to differences in the three input components:

$$(22) \qquad \frac{\ln\left(\prod_{i=1}^{5} h_i \Big/ \prod_{j=n-4}^{n} h_j\right)}{\ln\left(\prod_{i=1}^{5} y_i \Big/ \prod_{j=n-4}^{n} y_j\right)} + \frac{\ln\left(\prod_{i=1}^{5} \left(k_i / y_i\right)^{\frac{\alpha}{1-\alpha}} \Big/ \prod_{j=n-4}^{n} \left(k_j / y_j\right)^{\frac{\alpha}{1-\alpha}}\right)}{\ln\left(\prod_{i=1}^{5} y_i \Big/ \prod_{j=n-4}^{n} y_j\right)} + \frac{\ln\left(\prod_{i=1}^{5} A_i \Big/ \prod_{j=n-4}^{n} A_j\right)}{\ln\left(\prod_{i=1}^{5} y_i \Big/ \prod_{j=n-4}^{n} y_j\right)} = 1$$

where n is the sample size and countries $i, \ldots, j, \ldots, n$ are ranked according to output per worker.

To calibrate the macroeconomic production function, I assume a production elasticity of physical capital of $\alpha = 1/3$, which is the standard figure used for parameterization in the literature. It broadly resembles the share of physical capital in factor income as reported in national income accounts of developed countries (Maddison 1987), and it also seems to apply for developing countries once the labor income of the self-employed and other proprietors is properly accounted for (Gollin 1998).

Data on y and k are taken from Summers and Heston's (1991) Penn World Table, Version 5.6a (1994). Output per worker y is measured in 1990 or the next available year. The 1990 value of the stock of physical capital K is constructed by the perpetual inventory method based on annual investment rates and an assumed depreciation rate of 6 percent. The initial value for K is estimated by $I_t/(g_{t+10} + \delta)$, where I_t is the first year for which investment data are available, g_{t+10} is the average growth rate of investment in the subsequent decade, and δ is the depreciation rate (cf. Hall and Jones 1999). The figures for labor L in 1990 are derived by multiplying per capita output with population and dividing by output per worker.

Global Evidence

Table 2a presents the covariance measure for the broadest sample of countries for which the relevant data is available. The sample size of 132 countries is determined by the availability of investment data in the Penn World Tables to construct the physical capital stock. The first row begins with the first specification based on Mincerian human capital theory as used by Hall and Jones (1999), h^{HJ}, where 21 percent of the international variation in output per worker is accounted for by differences in human capital per worker. Since another 19 percent can be attributed to differences in the physical capital-output ratio, 60 percent remain as residual total factor productivity. With the human capital specification h^M, which attributes rates of return to years of schooling through equation (13) instead of equation (16) and uses social rates of return estimated by the elaborate discounting method, 33 percent of development differences are accounted for by human capital differences. Using country-specific social rates of return in the specification h^r, the share attributed to human capital is only 18 percent.

Since cognitive skills are not well proxied by measures of mere school quantities or country-specific rates of return to education, results based on the quality-adjusted human capital specification h^Q are reported in the last row of Table 2a. The adjustment of the human capital specification for differences in the quality of education boosts the share of variation in development levels attributed to human capital differences to 45 percent. This evidence shows that the assumption implicit in all previous specifications, that differences in educational quality can be neglected in the specification of human capital stocks, can give rise to misleading results on the development effect of human capital in development accounting studies.

The results based on the five-country measure, reported in Table 2b, confirm the results based on the covariance method. The share attributed to human capital is slightly higher with the five-country measure for all the specifications reported, and it is higher with h^r than with h^{HJ}. With h^Q, the five-country measure attributes 47 percent of the variation in development levels to human capital differences.

Table 3 shows the robustness of the calculated development impact of quality-adjusted human capital to further refinements and samples.[19] Using years of education in the population aged 25 and over (instead of 15 and over) leaves the human capital share unchanged. Recalculating the development accounting exercise for the year 1980 yields a development share attributed to differences in h^Q of 42 percent. Since these results may be affected by the oil-price shocks in the 1970s, an additional sample excludes countries dependent on primary resources by excluding all countries whose value added in the mining sector accounts for more than 10 percent of total value added. In this sample of 115 countries, the share attributed to quality-adjusted human capital is 47 percent in 1980 and 48 percent in 1990.

Further sub-samples for the 1990 results reveal that the human capital share is understated by the use of non-original data. When countries with imputed values on

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19 Results on the human capital share for the other specifications and results of the five-country measure are reported in Appendix Table A2.

years of schooling s^{ATT}, on the quality index Q, or on either of them are excluded, the share of development variation accounted for by human capital exceeds 50 percent. The same is true when countries are excluded which never participated in one of the benchmark studies underlying the Penn World Tables. In the sample of PWT benchmark countries without imputed data, with a sample size of 64 countries, the share attributed to quality-adjusted human capital rises to 60 percent. Furthermore, of the 88 available values of the quality index Q, more than half had been projected in Hanushek and Kimko (2000) on the basis of observed country and education-system characteristics. When confining the sample to the 38 countries with original data on educational quality, the calculated human capital share is 51 percent. And when combining all the restrictions discussed, yielding a sample of 29 countries which participated in a PWT benchmark study and which do not have any imputed or projected human capital data, 61 percent of the international variation in the level of economic development are accounted for by differences in quality-adjusted human capital. All this shows that the development impact of human capital seems to be severely understated by previous human capital specifications and by misreported human capital data.

4.3 Evidence on the Residual

Within the world sample of countries, differences in the residual A still account for between 26 and 36 percent (depending on the inclusion of imputed human capital data) of the cross-country variance in economic development. This result may be due to three different causes. First, there may be cross-country technological differences, so that the "technical-progress view" on the relation between human capital and economic development (Section 4.1) may have explanatory power. Second, cross-country differences in total factor productivity may arise from other factors, notably institutional differences across countries. Third, the residual may be caused by data recording errors, giving rise to attenuation bias in the shares attributed to the factor inputs, in which case the residual would not reflect real cross-country differences in total factor productivity.

Human Capital Stocks and Technical Differentiation

To estimate whether the recognition of the "technical-progress view" on the relationship between human capital and growth can add to an understanding of the residual, I use a simple conclusion of this view. If a higher stock of human capital caused a country's rate of technological progress to be higher than that of other countries with lower stocks of human capital, then the level of total factor productivity in the former countries - increased by technological advances - should be superior to the total factor productivity used in the latter countries. It follows by integration from equation (20) that the level of total factor productivity *A* should be a positive function of the stock of human capital, and at an increasing rate:

(23) $$A_i = A_{i0} e^{\psi(h_i)t} .$$

Therefore, the stock of human capital and the level of total factor productivity of a country should be positively correlated.

Calculating the level of total factor productivity as the residual in the neoclassical framework of equation (18), where $A_i = y_i \Big/ \left[\left(k_i / y_i \right)^{\frac{\alpha}{1-\alpha}} h_i \right]$ reflects what is left over of development differences after accounting for differences in factor inputs, in principle allows for a positive correlation between the level of total factor productivity and the human capital input. This constrasts with the regression methodology used in Mankiw et al. (1992), where total factor productivity is reflected in a regression residual which by construction is uncorrelated with the inputs (and by construction does not systematically differ across countries). By looking at the correlation between the residual *A* and the human capital stock *h*, the addition of the "technical-progress view" to an understanding of the residual in the development-accounting framework can be estimated.

As can be seen in Table 4, there is indeed some correlation between the residual *A* and the human capital specifications which ignore quality differences, h^{HJ} and h^{M}. However, when differences in educational quality are accounted for in the human capital stock h^{Q}, there is no longer any correlation between the residual and the stock of human capital.[20] This evidence suggests that while the human-capital-augmented neoclassical growth model is able to explain a substantial amount of the cross-country dispersion in development levels, the effect of the stock of human capital on economic development working through technical differentiation, as stressed by "technical-progress view," does not seem to add to an explanation of international differences in development levels.

Since with human capital specification h^Q, the residual is also uncorrelated with the physical capital component, international differences in the level of technology driven by human or physical capital stocks do not add to an understanding of the residual. This suggests the implication that this residual in cross-country productivity differences may not reflect differences in the technology used, corroborating the argumentation that, by the very nature of technological knowledge, all countries should in principle have access to the same technologies (Section 4.1). When neglecting potential attenuation bias in the results and assuming that the residual reflects real differences in the level of total factor productivity, these differences would then have to be caused by other cross-country differences which affect the productivity with which production factors are put to use. One causal factor which suggests itself are cross-country differences in the basic institutions which constitute the framework within which individuals produce and interact economically (cf. Hall and Jones 1999).

OECD-Sample Development Accounting Results

An indirect way to test whether international differences in residual total factor productivity in the world sample may reflect institutional differences is to look at a sample of countries in which such fundamental institutional differences do not exist. One such sample is arguably the sample of OECD countries, which share common basic institutional features which allow markets to function properly. When evaluated relative to many developing countries, OECD countries all have comparatively reliable legal frameworks securing private property rights, freedom of contracting, agencies ensuring competitive markets, market-friendly policies, and internal monetary stability. They also exhibit a relatively high degree of openness to trade and capital mobility which enables them to access similar technologies. Because of these similar institutional frameworks, there should be no differences in residual total factor productivity among OECD countries, with all countries producing on a common macroeconomic production function and differences in factor inputs sufficing to explain differences in development levels among these countries.

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[20] There is also no correlation when considering the non-linear form of the relationship as in equation (23): The correlation between $\ln(A)$ and h^Q is -0.140.

I use the sample of all OECD countries in 1990 except Luxembourg, for which no schooling quantity data is available. With output per worker in Turkey at less than a quarter of the US value and in Portugal and Greece at less than half the US value, there is a sizable variation in development levels to be explained in this sample. One advantage of the OECD sample over the world sample is that data should be recorded more accurately, so that data quality problems should be relatively small.

As the results based on the covariance measure presented in Table 5a reveal, the share of development variation accounted for by differences in human capital stocks is larger in the OECD sample than in the world sample. With specification h^{HJ}, the share attributed to human capital is 39 percent, with h^{M} 70 percent, with h^{r} 50 percent, and with h^{Q} 100 percent. That is, the covariance between the quality-adjusted human capital specification and output per worker in the OECD sample is just as large as the variance of output per worker, so that the whole variation in development levels can be accounted for by differences in quality-adjusted human capital. This result is confirmed by the five-country measure (Table 5b).

When the human capital specification accounts for differences in educational quality, the development accounting evidence suggests that OECD countries are broadly producing on a common level of total factor productivity.[21] The evidence reveals that the "neoclassical view" on the relationship between human capital and economic development yields a model which fits the data well. As an explanation of the differences in output per worker among OECD countries, the human-capital-augmented neoclassical growth model suffices. The "technical-progress view" on growth effects of human capital does not add to an understanding of the cross-country dispersion in development levels. The OECD results have an indication that the residual in the world evidence may be either due to poor data quality or due to differences in basic institutions governing the market processes.

[21] This result is also confirmed by the fact that there is no correlation between total factor productivity A and output per worker y in the OECD sample when human capital is specified as h^{Q} (the correlation coefficient is -0.09).

4.4 Data Recording Error versus Specification Error

Recent studies by Krueger and Lindahl (2000) and de la Fuente and Doménech (2000) have argued that there are serious data recording errors in the data on average years of schooling which lead to biased estimates of growth effects. As argued in Section 2.4, data quality may not be a major problem for cross-country level comparisons in 1990, because basically all observations at least in the OECD sample are direct census observations. To assess the importance of data quality problems in human capital measurement relative to the specification problems stressed in this paper, I compare development accounting results based on the three available data sets on average years of schooling in the population aged 15 and over which have been constructed on the basis of the attainment census method: the Barro and Lee (1996) data set, the Barro and Lee (2000) data set, and the de la Fuente and Doménech (2000) data set. Barro and Lee (2000) improve on the earlier data set by taking account of changes in the duration of schooling cycles and by a refined fill-in procedure for missing observations. De la Fuente and Doménech (2000) thoroughly revise the Barro and Lee (1996) data set for the OECD sample by using additional national data sources and deleting data inconsistencies.

When comparing the covariance-measure results based on the Barro and Lee (1996) data set in Table 6a to the results in Table 2a which are based on the revised Barro and Lee (2000) data set, it is obvious that the improvement in data quality had a minor impact on the development accounting results. The estimated share in output variation accounted for by differences in quality-adjusted human capital is half a percentage point higher in the case of the revised data set. The more thorough revision of the OECD data set by de la Fuente and Doménech (2000) has a larger effect on the development accounting results, but the difference in the share attributed to quality-adjusted human capital is still only 4 percentage points (Table 6b).[22] The effect on development accounting results of having improved human capital data seems to be minor relative to specification effects of using superior rate of return estimates and adjusting for educational quality. While improving on the recording of educational data is indeed a worthy issue, the recording issue of considering *data* quality seems to be less important

22 These results based on the covariance measure are confirmed by the five-country measure.

for development accounting studies than the specification issue of considering *human capital* quality.

5 Conclusion

The review of human capital specification has shown how the implementation of the concept of human capital has evolved in the empirical growth literature. In light of the differences among the different specifications, one should not wonder that different studies have found very different results on growth and development effects of human capital. The empirical results presented in this paper reveal that two crucial aspects of human capital specification are the correct inclusion of rates of return to education and the consideration of the quality of education. International differences in quality-adjusted human capital can account for about half the global dispersion of development levels and for virtually all the development dispersion among OECD countries within the framework of a simple human-capital-augmented neoclassical model of economic growth and development.

While this paper has focused on education as a means to accumulate human capital, an encompassing specification of human capital should consider the whole range of investments that people make to improve their productivity. In addition to formal education, these investments also include informal education acquired parallel to schooling, skills acquired after schooling through training on the job, and the experience gained through learning by doing. Furthermore, medical care, nutrition, and improvements in working conditions which avoid activities with high accident rates can be viewed as investments to improve health. While age less pre-schooling and schooling years has been used as a proxy for experience and life expectancy or infant mortality rates as a proxy for health status, these are probably not very good measures of the productively available human capital accumulated through after-school skill acquisition and through health investments. A further complication lies in the fact that knowledge can not only be gained, but also lost after it has been acquired in school. Nevertheless, the focus on the mere formal education component of human capital seems warranted, also because education increases people's ability to learn later in live and to live healthier lives.

Even more, education is an especially crucial aspect in development because it is not only important for human capital in the narrow sense that it augments future production possibilities, but also for human capabilities in the broader sense of ability and freedom of people to lead the kind of lives they value. When understanding development as a broader concept of freedom expansion as in Sen (1999), where economic growth is not an end in itself but a means to expanding the freedoms that people enjoy, the benefits of education exceed its role as human capital in economic production. These additional benefits of education as valued by the broader human-capability perspective include the abilities to read, communicate, and argue, to choose in a more informed way, or to be taken more seriously by others.

As a development accounting study, this paper has taken a mainly descriptive approach in accounting for the "proximate" causes of international differences in levels of economic development - human capital, physical capital, and residual total factor productivity. To search for "ultimate" causes of economic development, one has to go beyond development accounting and look at what lies behind productivity and the accumulation of human and physical capital. Still, the development accounting results give a hint on where to look for these deeper causes. For example, since educational quality seems to be a major factor in the stock of human capital, research on the causes of differences in the quality of education seems to be a fertile part of growth research. The evidence in Wößmann (2000) suggests that cross-country differences in human capital quality are due to differences in institutional features of the education systems rather than due to differences in educational spending. More generally, as the difference in the development accounting results between the world and OECD-sample results suggests, the analysis of institutions as an underlying cause of economic development seems promising (cf. Olson 1996, Hall and Jones 1999).

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Appendix

Table A1: Data

Relative to the United States. Absolute U.S. values reported in the first row.

	[1] l^1	[2] e	[3] e^{MRW}	[4] s^{PIM}	[5] s^{PRO}	[6] s^{ATT}	[7] s^{DD}	[8] h^{HJ}	[9] h^{M}	[10] h^{r}	[11] h^{Q}	y	k
United States (Abs.)	-	91.1	11.9	11.6	12.1	11.7	12.9	3.3	6.9	4.3	6.9	36 771	90 632
Luxembourg	-	-	0.420	-	0.571	-	-	0.820	0.662	0.708	0.615	1.031	1.242
United States	-	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Qatar	0.770	0.840	-	-	-	-	-	0.698	0.484	0.598	0.444	0.995	-
United Arab E.	0.770	0.776	-	-	-	-	-	0.698	0.484	0.598	0.444	0.995	-
Canada	-	1.093	0.891	0.862	0.826	0.936	0.991	0.950	0.898	0.864	1.216	0.935	0.993
Switzerland	-	0.783	0.403	0.599	-	0.864	0.971	0.897	0.804	0.819	1.370	0.892	1.256
Belgium	-	0.901	0.782	0.721	0.774	0.756	0.756	0.823	0.704	0.862	0.997	0.863	0.887
Netherlands	-	0.947	0.899	0.725	0.784	0.745	0.848	0.816	0.665	0.604	0.856	0.850	0.890
Italy	-	0.773	0.597	0.684	0.756	0.552	0.620	0.665	0.446	0.529	0.475	0.838	0.949
France	-	0.910	0.748	0.732	0.789	0.592	0.842	0.697	0.486	0.564	0.616	0.826	0.978
Australia	-	0.834	0.824	0.654	0.722	0.884	0.951	0.911	0.888	0.923	1.427	0.824	1.011
Germany, West	-	0.833	0.706	0.731	0.855	0.827	1.006	0.871	0.684	0.733	0.728	0.803	0.950
Bahamas	0.980	-	-	-	-	-	-	0.717	0.514	0.881	0.530	0.798	-
Norway	-	0.899	0.840	0.817	0.764	0.985	0.794	0.988	1.052	0.862	2.231	0.795	1.062
Sweden	-	0.813	0.664	0.848	0.797	0.810	0.807	0.859	0.735	0.776	1.062	0.772	0.832
Finland	-	0.980	0.966	0.844	0.896	0.799	0.765	0.852	0.734	0.763	1.141	0.744	1.052
Oman	-	0.600	0.227	-	-	-	-	0.617	0.402	0.506	0.341	0.732	0.540
United Kingdom	-	0.818	0.748	0.879	0.703	0.747	0.847	0.817	0.695	0.704	1.175	0.728	0.599
Austria	-	0.870	0.672	0.754	0.709	0.661	0.848	0.757	0.523	0.599	0.685	0.726	0.821
Spain	-	0.920	0.672	0.616	0.802	0.549	0.550	0.662	0.454	0.588	0.515	0.717	0.739
Puerto Rico	-	-	-	-	-	-	-	0.633	0.427	1.136	0.397	0.711	0.477
Kuwait	0.760	-	0.807	-	0.572	0.510	-	0.633	0.372	0.490	0.229	0.707	-
New Zealand	-	0.877	1.000	0.762	0.767	0.958	0.938	0.967	1.049	1.345	2.468	0.691	0.879
Iceland	-	0.886	0.857	0.791	0.708	0.691	-	0.781	0.609	0.664	0.697	0.679	0.760
Denmark	-	0.894	0.899	0.787	0.571	0.816	0.847	0.863	0.751	0.775	1.270	0.679	0.796
Singapore	0.890	0.673	0.756	0.631	0.570	0.507	-	0.631	0.420	0.428	0.746	0.663	0.664
Ireland	-	0.886	0.958	1.083	0.731	0.748	0.729	0.818	0.669	0.712	0.748	0.654	0.637
Israel	-	0.839	0.798	0.620	0.830	0.798	-	0.851	0.781	0.840	1.029	0.647	0.560
Saudi Arabia	0.590	0.542	0.261	-	0.244	-	-	0.617	0.402	0.506	0.341	0.640	0.422
Hong Kong	0.910	-	0.605	-	0.645	0.780	-	0.839	0.682	1.159	1.560	0.621	0.361
Japan	-	0.844	0.916	0.946	0.783	0.763	0.871	0.828	0.687	0.528	1.279	0.615	0.785
Bahrain	0.820	0.903	1.017	-	-	0.423	-	0.571	0.354	0.459	0.226	0.595	-
Trinidad & Tobago	0.970	0.761	0.739	-	0.489	0.610	-	0.713	0.517	0.661	0.512	0.541	0.420
Taiwan	-	-	-	-	0.386	0.679	-	0.774	0.581	1.301	0.771	0.501	0.335
Malta	-	0.827	0.597	-	0.565	-	-	0.737	0.567	0.655	0.766	0.495	0.378
Cyprus	-	0.796	0.689	0.660	-	0.742	-	0.814	0.662	0.445	0.651	0.491	0.440
Greece	-	0.845	0.664	0.753	0.695	0.681	0.613	0.775	0.605	0.654	0.686	0.482	0.481
Venezuela	0.900	0.772	0.588	0.569	0.571	0.422	-	0.570	0.357	0.615	0.308	0.474	0.446
Mexico	0.880	0.718	0.555	0.511	0.584	0.572	-	0.681	0.480	0.683	0.377	0.463	0.312
Portugal	-	0.785	0.487	0.493	0.539	0.418	0.497	0.567	0.342	0.436	0.327	0.452	0.352
Korea, Rep.	0.970	0.866	0.857	0.665	0.657	0.847	-	0.885	0.789	0.908	1.207	0.436	0.331
Syria	0.660	0.752	0.739	-	0.548	0.435	-	0.579	0.361	0.510	0.262	0.432	0.261
U.S.S.R. (Rus. Fed.)	-	0.923	-	-	-	-	-	0.737	0.567	0.749	0.713	0.417	0.630
Barbados	0.970	-	1.017	-	0.663	0.674	-	0.769	0.576	0.726	0.844	0.400	0.209
Argentina	0.960	-	0.420	0.652	0.664	0.693	-	0.782	0.638	0.450	0.674	0.365	0.359
Bulgaria	-	0.801	-	-	-	-	-	0.691	0.509	0.682	0.526	0.349	-
Jordan	0.820	0.598	0.908	0.424	0.618	0.506	-	0.630	0.407	0.568	0.369	0.344	0.228
Malaysia	0.800	0.645	0.613	0.534	0.474	0.514	-	0.636	0.430	0.661	0.512	0.341	0.276
Algeria	0.550	0.711	0.378	0.354	0.385	0.362	-	0.531	0.310	0.447	0.229	0.331	0.324
Iraq	0.520	-	0.622	0.360	0.377	0.278	-	0.469	0.262	0.365	0.206	0.323	0.314
Chile	0.940	-	0.647	0.618	0.576	0.593	-	0.698	0.515	0.438	0.284	0.322	0.272
Uruguay	0.970	0.847	0.588	0.679	0.634	0.604	-	0.707	0.507	0.775	0.587	0.322	0.253
Fiji	0.890	0.806	0.681	-	0.549	0.669	-	0.764	0.636	0.958	0.910	0.321	0.216
Iran	-	0.720	0.546	0.328	0.476	0.338	-	0.515	0.294	0.439	0.192	0.310	0.253
Belize	0.300	-	-	-	-	-	-	0.594	0.383	0.567	0.333	0.305	-
Brazil	0.810	0.739	0.395	0.380	0.458	0.342	-	0.519	0.305	0.761	0.260	0.300	0.239

(to be continued)

Table A1 (continued)

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]		
	l	e	e^{MRW}	s^{PIM}	s^{PRO}	s^{ATT}	s^{DD}	h^{HJ}	h^{M}	h^{r}	h^{Q}	y	k
Hungary	-	0.743	-	-	-	0.761	-	0.826	0.764	0.818	1.276	0.294	0.389
Mauritius	0.800	0.645	0.613	-	0.522	0.474	-	0.607	0.396	0.692	0.472	0.277	0.105
Colombia	0.900	0.622	0.513	0.436	0.540	0.400	-	0.556	0.333	0.520	0.284	0.275	0.174
Costa Rica	0.940	0.684	0.588	-	0.681	0.473	-	0.606	0.394	0.448	0.389	0.273	0.192
Yugoslavia	-	-	-	-	-	0.601	-	0.705	0.541	0.291	0.662	0.272	0.465
South Africa	0.800	0.874	0.252	-	-	0.460	-	0.596	0.399	0.730	0.440	0.261	0.216
Namibia	-	-	-	-	-	-	-	0.520	0.305	0.519	0.270	0.259	0.269
Seychelles	-	-	-	-	-	-	-	0.555	0.340	0.538	0.316	0.248	0.154
Ecuador	0.870	0.772	0.605	0.493	0.725	0.503	-	0.627	0.413	0.529	0.347	0.246	0.229
Tunisia	0.600	0.677	0.361	0.415	0.468	0.335	-	0.513	0.296	0.429	0.269	0.241	0.115
Turkey	0.790	0.606	0.462	0.387	0.523	0.353	-	0.525	0.309	0.434	0.276	0.235	0.186
Gabon	0.560	-	0.218	-	0.663	-	-	0.555	0.340	0.538	0.316	0.219	0.231
Yemen	-	-	0.050	-	-	0.126	-	0.370	0.191	0.266	0.179	0.219	0.077
Panama	0.890	0.739	0.975	0.644	0.661	0.688	-	0.779	0.619	0.885	0.619	0.218	0.192
Czechoslovakia	-	0.787	-	-	-	-	-	0.737	0.567	0.655	0.654	0.210	0.277
Suriname	0.920	-	0.681	-	0.503	-	-	0.633	0.427	0.564	0.397	0.203	0.205
Poland	-	0.829	-	-	-	0.806	-	0.857	0.858	1.059	1.673	0.203	0.381
Guatemala	0.530	-	0.202	0.303	0.304	0.259	-	0.455	0.256	0.390	0.236	0.202	0.083
Reunion	-	-	-	-	-	-	-	0.555	0.340	0.538	0.316	0.198	0.158
Dominican Rep.	0.800	-	0.487	-	-	0.378	-	0.541	0.320	0.483	0.283	0.188	0.145
Egypt	0.480	0.737	0.588	0.412	0.471	0.363	-	0.532	0.307	0.483	0.222	0.187	0.038
Peru	0.860	0.854	0.672	0.565	0.657	0.529	-	0.647	0.434	0.641	0.381	0.186	0.195
Morocco	-	-	0.303	0.208	0.288	-	-	0.553	0.336	1.387	0.276	0.184	0.072
Thailand	0.930	-	0.370	0.493	0.456	0.476	-	0.607	0.414	1.065	0.409	0.184	0.095
Solomon Is.	-	-	-	-	-	-	-	0.526	0.308	0.522	0.289	0.178	-
Botswana	0.650	0.739	0.244	-	0.292	0.455	-	0.593	0.396	2.135	0.287	0.178	0.108
Western Samoa	-	-	-	-	-	-	-	0.591	0.377	0.583	0.361	0.175	-
Grenada	-	-	-	-	-	-	-	0.594	0.383	0.567	0.333	0.174	-
Paraguay	0.910	0.615	0.370	0.500	0.510	0.523	-	0.642	0.442	0.709	0.376	0.174	0.111
Swaziland	0.720	0.720	0.311	-	0.447	0.450	-	0.590	0.398	0.685	0.346	0.171	0.094
Dominica	-	-	-	-	0.550	-	-	0.594	0.383	0.567	0.333	0.168	-
Tonga	-	-	-	-	-	-	-	0.591	0.377	0.583	0.361	0.164	-
St. Vincent & Gre.	-	-	-	-	-	-	-	0.594	0.383	0.567	0.333	0.158	-
Sri Lanka	0.890	0.728	0.697	0.540	0.499	0.517	-	0.638	0.421	0.728	0.382	0.156	0.071
El Salvador	0.690	0.620	0.328	0.428	0.349	0.362	-	0.531	0.324	0.454	0.228	0.149	0.062
St. Lucia	-	-	-	-	-	-	-	0.594	0.383	0.567	0.333	0.145	-
Bolivia	0.790	0.693	0.412	0.544	0.444	0.428	-	0.574	0.364	0.368	0.249	0.145	0.090
Vanuatu	-	-	-	-	-	-	-	0.591	0.377	0.583	0.361	0.143	-
Jamaica	0.830	0.697	0.941	0.693	0.488	0.404	-	0.558	0.336	0.457	0.347	0.140	0.139
Indonesia	0.820	0.673	0.345	0.381	0.370	0.341	-	0.518	0.302	0.494	0.285	0.137	0.099
Djibouti	0.410	0.215	-	-	-	-	-	0.520	0.305	0.519	0.270	0.133	0.069
Bangladesh	0.350	0.381	0.269	0.269	0.288	0.187	-	0.407	0.217	0.358	0.210	0.130	0.018
Philippines	0.940	0.847	0.891	0.667	0.734	0.620	-	0.721	0.532	0.562	0.369	0.130	0.089
Pakistan	0.340	0.339	0.252	0.182	0.210	0.353	-	0.525	0.293	0.369	0.276	0.126	0.043
Congo	0.680	0.822	0.319	-	-	0.437	-	0.580	0.357	0.621	0.386	0.122	0.046
Honduras	0.690	-	0.311	0.383	0.467	0.358	-	0.528	0.317	0.508	0.235	0.121	0.069
Nicaragua	0.640	0.617	0.487	-	0.498	0.311	-	0.494	0.284	0.430	0.215	0.113	0.089
Romania	-	0.729	-	-	-	-	-	0.691	0.509	0.682	0.526	0.112	0.119
Mongolia	0.800	0.719	-	-	-	-	-	0.591	0.377	0.583	0.361	0.107	-
India	0.480	0.568	0.429	0.305	0.393	0.349	-	0.523	0.308	0.654	0.203	0.088	0.045
Cote d'Ivoire	0.340	-	0.193	0.181	0.340	-	-	0.520	0.305	0.519	0.270	0.084	0.047
Papua New Guinea	0.680	-	0.126	-	0.232	0.196	-	0.412	0.226	0.319	0.180	0.082	0.068
Guyana	0.970	-	0.983	-	0.514	0.484	-	0.614	0.416	0.689	0.462	0.081	0.149
Laos	0.520	-	-	-	-	-	-	0.526	0.308	0.522	0.289	0.078	-
Cape Verde Is.	0.630	0.605	-	-	-	-	-	0.520	0.305	0.519	0.270	0.075	0.070
Cameroon	0.570	0.577	0.286	0.269	0.449	0.262	-	0.457	0.258	0.432	0.244	0.068	0.031
Sierra Leone	0.270	0.314	0.143	0.190	0.164	0.182	-	0.403	0.215	0.360	0.199	0.068	0.005
Zimbabwe	0.820	0.754	0.370	0.389	0.402	0.429	-	0.575	0.356	0.726	0.311	0.066	0.047
Senegal	0.290	0.338	0.143	0.173	0.205	0.193	-	0.410	0.222	0.369	0.207	0.065	0.014
Sudan	0.400	0.341	0.168	0.160	0.173	0.140	-	0.378	0.197	0.322	0.185	0.063	0.041
Nepal	0.240	0.603	0.193	-	0.168	0.132	-	0.373	0.190	0.311	0.186	0.062	0.016
China	0.780	0.587	-	0.448	-	0.498	-	0.624	0.416	0.722	0.618	0.060	0.050
Liberia	0.340	-	0.210	-	0.267	0.183	-	0.404	0.215	0.487	0.199	0.058	0.033

(to be continued)

Table A1 (continued)

	[1] l	[2] e	[3] e^{MRW}	[4] s^{PIM}	[5] s^{PRO}	[6] s^{ATT}	[7] s^{DD}	[8] h^{HJ}	[9] h^{M}	[10] h^{r}	[11] h^{Q}	y	k
Nigeria	0.490	-	0.210	0.210	0.166	-	-	0.447	0.249	0.426	0.228	0.057	0.034
Lesotho	0.670	0.665	0.168	-	0.404	0.334	-	0.512	0.312	0.366	0.339	0.057	0.033
Zambia	0.730	0.618	0.202	0.388	0.317	0.356	-	0.527	0.325	0.608	0.273	0.056	0.059
Haiti	0.410	-	0.160	0.226	0.220	0.248	-	0.447	0.249	0.406	0.226	0.054	0.018
Benin	-	0.333	0.151	-	0.193	0.166	-	0.393	0.209	0.358	0.194	0.052	0.019
Ghana	0.580	0.493	0.395	0.391	0.319	0.308	-	0.492	0.278	0.422	0.208	0.051	0.012
Kenya	0.720	0.637	0.202	0.356	0.285	0.311	-	0.494	0.292	0.518	0.227	0.051	0.028
Gambia	0.340	-	0.126	-	0.128	0.138	-	0.377	0.196	0.332	0.184	0.047	0.014
Mauritania	0.350	0.285	0.084	0.573	0.085	0.206	-	0.419	0.230	0.402	0.209	0.045	0.037
Somalia	-	-	0.092	-	0.068	-	-	0.447	0.249	0.398	0.224	0.045	0.022
Guinea	0.310	0.211	-	-	-	-	-	0.447	0.249	0.444	0.224	0.043	0.011
Togo	0.450	0.598	0.244	-	-	0.250	-	0.449	0.249	0.442	0.212	0.043	0.029
Madagascar	-	0.462	0.218	0.300	0.356	-	-	0.447	0.249	0.444	0.224	0.042	0.004
Mozambique	0.350	-	0.059	0.226	0.174	0.077	-	0.342	0.174	0.288	0.162	0.042	0.005
Rwanda	0.540	-	0.034	0.239	0.268	0.179	-	0.401	0.220	0.381	0.202	0.042	0.009
Bhutan	0.370	-	-	-	-	-	-	0.526	0.308	0.522	0.289	0.041	-
Guinea-Biss.	0.500	-	-	-	0.190	0.055	-	0.330	0.165	0.270	0.161	0.040	0.028
Angola	-	0.378	0.151	0.157	0.305	-	-	0.520	0.305	0.519	0.270	0.040	0.007
Myanmar (Burma)	0.810	0.494	0.294	0.222	0.409	0.211	-	0.422	0.228	0.377	0.220	0.037	0.012
Comoros	0.540	-	-	0.679	-	-	-	0.447	0.249	0.444	0.224	0.034	0.025
Central Afr. R.	0.500	0.345	0.118	-	0.295	0.200	-	0.415	0.223	0.388	0.183	0.033	0.010
Malawi	0.520	0.436	0.050	0.293	0.163	0.231	-	0.436	0.248	0.348	0.222	0.033	0.013
Chad	0.430	-	0.034	-	0.151	-	-	0.447	0.249	0.444	0.224	0.031	0.004
Uganda	0.570	0.437	0.092	0.216	0.243	0.278	-	0.469	0.271	1.672	0.239	0.031	0.004
Tanzania	0.620	0.371	0.042	0.216	0.152	0.237	-	0.440	0.251	0.439	0.225	0.031	0.013
Zaire (Congo, D. R.)	0.720	-	0.303	0.344	0.358	0.239	-	0.441	0.246	0.436	0.212	0.030	0.008
Mali	0.250	0.151	0.084	0.097	0.119	0.057	-	0.331	0.165	0.271	0.161	0.030	0.008
Burundi	0.310	0.348	0.034	-	0.143	0.118	-	0.364	0.190	0.321	0.180	0.029	0.007
Burkina Faso	0.160	0.181	0.034	-	0.061	-	-	0.447	0.249	0.444	0.224	0.029	0.011
Niger	0.120	0.159	0.042	-	0.069	0.070	-	0.338	0.170	0.280	0.165	0.028	0.013
Ethiopia	0.310	0.206	0.092	0.049	0.094	-	-	0.447	0.249	0.415	0.224	0.019	0.004

Note: [1] l (column [1]): Absolute value of the adult literacy rate.

Table A2a: Share of Human Capital: Further Samples

Covariance Measure: $\dfrac{\operatorname{cov}(\ln(y),\ln(h^X))}{\operatorname{var}(\ln(y))}$

	h^{HJ}	h^{M}	h^{r}	h^{Q}
Population 25 and over	0.22	0.34	0.20	0.45
1980	0.21	0.33	0.19	0.42
1980: low mining share	0.23	0.36	0.22	0.47
Samples:				
Low mining share	0.22	0.35	0.19	0.48
Non-imputed s^{ATT}	0.23	0.37	0.19	0.51
Non-imputed Q	0.20	0.34	0.16	0.51
Non-imputed s^{ATT} and Q	0.20	0.33	0.16	0.52
PWT benchmark study (BS)	0.22	0.36	0.19	0.52
BS, non-imputed s^{ATT} and Q	0.20	0.35	0.13	0.60
Non-projected Q	0.21	0.34	0.14	0.51
BS, no-imp. s^{ATT}, no-proj. Q	0.19	0.34	0.11	0.61

Note: For h^{HJ}, h^{M}, h^{r}, and h^{Q}, see equations (13) to (16).

Table A2b: Share of Human Capital: Further Samples

Five-Country Measure: $\ln\left(\prod_{i=1}^{5} h_i^X \Big/ \prod_{j=n-4}^{n} h_j^X\right) \Big/ \ln\left(\prod_{i=1}^{5} y_i \Big/ \prod_{j=n-4}^{n} y_j\right)$

with n = sample size, countries i, ..., j, ..., n ranked according to y

	h^{HJ}	h^{M}	h^{r}	h^{Q}
Population 25 and over	0.24	0.39	0.26	0.47
1980	0.19	0.30	0.18	0.36
1980: low mining share	0.23	0.36	0.22	0.44
Samples:				
Low mining share	0.24	0.39	0.26	0.47
Non-imputed s^{ATT}	0.25	0.40	0.18	0.51
Non-imputed Q	0.23	0.39	0.23	0.51
Non-imputed s^{ATT} and Q	0.24	0.39	0.22	0.54
PWT benchmark study (BS)	0.22	0.36	0.23	0.44
BS, non-imputed s^{ATT} and Q	0.19	0.35	0.15	0.47
Non-projected Q	0.21	0.36	0.20	0.49
BS, no-imp. s^{ATT}, no-proj. Q	0.14	0.36	0.10	0.37

Note: For h^{HJ}, h^{M}, h^{r}, and h^{Q}, see equations (13) to (16).

Table 1: Correlation between Human Capital Specifications

Correlation coefficents; number of joint observations in brackets below

	[1] l	[2] e	[3] e^{MRW}	[4] s^{PIM}	[5] s^{PRO}	[6] s^{ATT}	[7] s^{DD}	[8] h^{HJ}	[9] h^{M}	[10] h^{r}	[11] h^{Q}
[1] l	1 [96]										
[2] e	0.828 [67]	1 [103]									
[3] e^{MRW}	0.738 [83]	0.817 [90]	1 [117]								
[4] s^{PIM}	0.770 [55]	0.858 [69]	0.863 [81]	1 [83]							
[5] s^{PRO}	0.846 [79]	0.902 [83]	0.872 [108]	0.878 [79]	1 [111]						
[6] s^{ATT}	0.841 [77]	0.830 [86]	0.819 [102]	0.890 [76]	0.896 [96]	1 [108]					
[7] s^{DD}	- [0]	0.300 [21]	0.383 [21]	0.345 [21]	0.471 [20]	0.791 [21]	1 [21]				
[8] h^{HJ}	0.789 [96]	0.809 [103]	0.806 [117]	0.863 [83]	0.872 [111]	0.999 [108]	0.789 [21]	1 [152]			
[9] h^{M}	0.759 [96]	0.736 [103]	0.753 [117]	0.822 [83]	0.819 [111]	0.973 [108]	0.697 [21]	0.976 [152]	1 [152]		
[10] h^{r}	0.395 [96]	0.447 [103]	0.344 [117]	0.373 [83]	0.361 [111]	0.574 [108]	0.579 [21]	0.558 [151]	0.554 [151]	1 [151]	
[11] h^{Q}	0.562 [96]	0.576 [103]	0.623 [117]	0.695 [83]	0.661 [111]	0.846 [108]	0.503 [21]	0.845 [151]	0.916 [151]	0.510 [151]	1 [151]

Table 2a: Human Capital and Economic Development: World Evidence

Covariance measure: $\dfrac{\operatorname{cov}(\ln(y),\ln(Z))}{\operatorname{var}(\ln(y))}$ with Z given in each column

	h^X	$(k/y)^{\frac{\alpha}{1-\alpha}}$	A	*Sample Size*
$X=$				
HJ	0.21	0.19	0.60	132
M	0.33	0.19	0.48	132
r	0.18	0.19	0.63	132
Q	0.45	0.19	0.36	132

Note: For h^{HJ}, h^M, h^r, and h^Q, see equations (13) to (16).

Table 2b: Human Capital and Economic Development: World Evidence

Five-Country Measure: $\ln\left(\prod_{i=1}^{5} Z_i \Big/ \prod_{j=n-4}^{n} Z_j\right) \Big/ \ln\left(\prod_{i=1}^{5} y_i \Big/ \prod_{j=n-4}^{n} y_j\right)$

with n = sample size, countries i, ..., j, ..., n ranked according to y, and Z given in each column

	h^X	$(k/y)^{\frac{\alpha}{1-\alpha}}$	A	*Sample Size*
$X=$				
HJ	0.24	0.19	0.57	132
M	0.39	0.19	0.42	132
r	0.26	0.19	0.56	132
Q	0.47	0.19	0.34	132

Note: For h^{HJ}, h^M, h^r, and h^Q, see equations (13) to (16).

Table 3: Quality-Adjusted Human Capital and Economic Development: Further Evidence

Covariance measure: $\frac{\mathrm{cov}(\ln(y),\ln(Z))}{\mathrm{var}(\ln(y))}$ with Z given in each column

	h^Q	$(k/y)^{\frac{\alpha}{1-\alpha}}$	A	*Sample Size*
Population 25 and over	0.45	0.19	0.36	132
1980	0.42	0.19	0.39	132
1980: low mining share	0.47	0.22	0.31	115
Samples:				
Low mining share	0.48	0.20	0.33	115
Non-imputed s^{ATT}	0.51	0.19	0.30	104
Non-imputed Q	0.51	0.15	0.34	88
Non-imputed s^{ATT} and Q	0.52	0.15	0.33	85
PWT benchmark study (BS)	0.52	0.22	0.27	82
BS, non-imputed s^{ATT} and Q	0.60	0.13	0.27	64
Non-projected Q	0.51	0.18	0.31	38
BS, no-imp. s^{ATT}, no-proj. Q	0.61	0.13	0.26	29

Table 4: Correlation with the Level of Productivity *A*

Correlation coefficents; all variables measured in logs

	h^X	$(k/y)^{\frac{\alpha}{1-\alpha}}$	y
X=			
HJ	0.575	0.286	0.898
M	0.337	0.140	0.786
r	0.071	0.313	0.852
Q	-0.043	-0.018	0.587

Note: For h^{HJ}, h^M, h^r, and h^Q, see equations (13) to (16).

Table 5a: Human Capital and Economic Development: OECD Sample

Covariance measure: $\dfrac{\mathrm{cov}(\ln(y),\ln(Z))}{\mathrm{var}(\ln(y))}$ with Z given in each column

	h^X	$(k/y)^{\frac{\alpha}{1-\alpha}}$	A	*Sample Size*
$X=$				
HJ	0.39	0.15	0.47	23
M	0.70	0.15	0.15	23
r	0.50	0.15	0.35	23
Q	1.00	0.15	-0.14	23

Note: For h^{HJ}, h^M, h^r, and h^Q, see equations (13) to (16).

Table 5b: Human Capital and Economic Development: OECD Sample

Five-Country Measure: $\ln\left(\prod_{i=1}^{5} Z_i \Big/ \prod_{j=n-4}^{n} Z_j\right) \Big/ \ln\left(\prod_{i=1}^{5} y_i \Big/ \prod_{j=n-4}^{n} y_j\right)$

with n = sample size, countries i, ..., j, ..., n ranked according to y, and Z given in each column

	h^X	$(k/y)^{\frac{\alpha}{1-\alpha}}$	A	*Sample Size*
$X=$				
HJ	0.38	0.11	0.51	23
M	0.72	0.11	0.17	23
r	0.61	0.11	0.28	23
Q	0.94	0.11	-0.05	23

Note: For h^{HJ}, h^M, h^r, and h^Q, see equations (13) to (16).

Table 6a: Alternative Schooling Quantity Data Sets: Barro and Lee (1996)

Covariance measure: $\frac{\text{cov}(\ln(y),\ln(Z))}{\text{var}(\ln(y))}$ with Z given in each column

	h^X	$(k/y)^{\frac{\alpha}{1-\alpha}}$	A	*Sample Size*
X=				
HJ	0.20	0.19	0.61	132
M	0.33	0.19	0.48	132
r	0.19	0.19	0.62	132
Q	0.44	0.19	0.37	132

Note: For h^{HJ}, h^M, h^r, and h^Q, see equations (13) to (16).

Table 6b: Alternative Schooling Quantity Data Sets: De la Fuente and Doménech (2000), OECD Sample

Covariance measure: $\frac{\text{cov}(\ln(y),\ln(Z))}{\text{var}(\ln(y))}$ with Z given in each column

	h^X	$(k/y)^{\frac{\alpha}{1-\alpha}}$	A	*Sample Size*
X=				
HJ	0.46	0.15	0.40	21
M	0.86	0.15	-0.01	21
r	0.68	0.15	0.17	21
Q	1.04	0.15	-0.19	21

Note: For h^{HJ}, h^M, h^r, and h^Q, see equations (13) to (16).