SPECIFYING HUMAN CAPITAL

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Abstract. A review of the measures of the stock of human capital used in empirical growth research – including adult literacy rates, school enrollment ratios, and average years of schooling of the working-age population – reveals that human capital is mostly poorly proxied. The simple use of the most common proxy, average years of schooling, misspecifies the relationship between education and the stock of human capital. Based on human capital theory, the specification of human capital is extended to allow for decreasing returns to education and for differences in the quality of a year of education. The different specifications give rise to hugely differing measures of the stock of human capital across countries, and development-accounting results show that misspecified human capital measures can lead to severe underestimation of the development effect of human capital.

Keywords. human capital measurement; years of schooling; Mincer specification; educational quality; development accounting. JEL Classification: O4, I2

1. Introduction

The acquisition of knowledge and skills is an investment in the sense that people forego consumption in order to increase future income. Because workers have invested in themselves to different extents through education, one hour of labour input does not yield the same output across all workers. Education increases future labour 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'.

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While these citations demonstrate an early awareness of the importance of human capital in the economics profession, 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.[1]

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. It should be clear from the outset that the paper does *not* give a survey of 'human capital and growth,' but that it pursues a much more limited task: to survey empirical specifications of measures of the stock of 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.' Likewise, Borghans *et al.* (2001, p. 375) state that 'in relation to th[e] far-reaching theoretical and practical importance [of skills], economic science is hampered by the fact that procedures for the empirical measurement of skills are comparatively under-developed.' A survey of human capital measurement, combined with a critique of commonly used proxies and suggestions for improvement, may thus be a helpful device at the current state of the literature.

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 are perfectly recorded, the measured variable may still be a poor measure of the true variable. These second measurement errors due to using an imperfect proxy for the true stock of human capital are the focus of this paper.

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 labour 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 survey and relate the different specifications of the human capital measure used in the literature, to show that there are potentially huge specification errors in the human capital proxies currently used in applied work, and to present theoretically founded improvements of the specification of human capital measures.

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, evaluates their merits and shortcomings, and shows how the different measures are interrelated. These measures include education-augmented labour 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 in part on Gundlach *et al.* (2002), 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.

A comparison of measures of the stock of human capital based on the different specifications reveals that for virtually all countries in the world, specification issues strongly matter for the estimated stock of human capital, both in absolute and relative terms (Section 4). A low cross-country correlation between the preferred quality-adjusted measure of human capital and previously used measures shows that there is much scope for misspecifcation of the human capital variable, and development-accounting results suggest that this misspecification may cause severe underestimation of the development impact of human capital in empirical growth research. Section 5 concludes.

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

2.1. *Education-Augmented Labour Input in Early Growth Accounting*

The only factor inputs which were accounted for in the earliest growth accounting studies were physical capital and labour. Thus, the total labour 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, footnote 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 labour input, and therefore a result of real capital formation of an important kind.'

Subsequent growth accounting studies tried to account for the heterogeneity of labour by considering differences in the quality of labour input. Labour 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 labour input to reflect differences in the quality of labour 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 labour is estimated by the use of earnings weights. Assuming that wage differences reflect differences in the marginal product of labour, differences in the wages earned by different labour force groups make it possible to measure differences in their human capital. By using data on the distribution of the labour force across worker categories and weighting each category by its relative average wages, an aggregate labour quality index is constructed which reflects differences in the labour 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 labour 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 labour 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 labour input categories which are then aggregated on the basis of wage weights to yield a constant quality measure of overall labour input. Dagum and Slottje (2000) combine this earnings-based method to calculate macroeconomic average stocks of human capital with a microeconomic estimation of human capital as a latent variable on the basis of survey data on a set of human-capital indicators. This allows them to calculate not only the average level of human capital, but also the distribution of human capital among households.

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 labour, difficulties in cross-country comparisons, stemming mainly from informational deficiencies and measurement differences, were not addressed. Therefore, measures of total labour input adjusted for quality differences, and especially education-augmented labour 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 labour 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:

$$l = \frac{M_A}{P_A} \tag{1}$$

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 labour force. Therefore, adult literacy rates can only stand for a minor part of the total stock of human capital. 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).

2.3. *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. 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. Enrollment ratios have been used to proxy for human capital in the seminal studies of Barro (1991) and Mankiw *et al.* (1992)[2] and in the sensitivity study by Levine and Renelt (1992), among many others.

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 labour 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 labour 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 labour force, which are determined by the difference between the human capital embodied in the labour force entrants and the human capital embodied in those who retire from the labour 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 labour force this year, but the human capital acquired by current students who might enter the labour 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 labour force because graduates may not participate in the labour 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 labour 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).[3]

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 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 labour 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 labour force. Educational attainment is clearly a stock variable, and it takes into account the total amount of formal education received by the labour 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; 2001), Benhabib and Spiegel (1994), Gundlach (1995), Islam (1995), Krueger and Lindahl (2001), O'Neill (1995), and Temple (1999b).[4]

2.4.1 *Perpetual Inventory Method*

Three main methods have been used in the construction of data sets on years of educational attainment in the labour 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 labour force at time T by

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

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 labour force, A_l is the lowest possible age of a person in the labour 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 labour 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:

$$s^{PIM} = \frac{S^{PIM}}{P_w}. \tag{4}$$

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.

2.4.2 *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 labour 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 labour force s for further countries and years T:

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

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:

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

where ε is an error term.[6]

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 labour force and lagged enrollment ratios is stable over time and across countries.

2.4.3 *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 labour 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 labour force can be calculated as

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

where n_a is the fraction of the labour 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 labour force) and D_a is the duration in years of the ath level of schooling.[7] For fractions of the labour 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 labour force (they use $n_a = N_a/P_A$ with P_A 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 labour 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 (2001) additionally account for variations in the duration D_a of schooling levels over time within a country.

De la Fuente and Doménech (2000; 2001) 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.

2.4.4 *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, especially as years-of-schooling data will turn out to be an important ingredient of a well-specified measure of human capital. 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 the only method that involves making parametric assumptions. It is based on the assumption that the relationship between average years of schooling in the labour force and lagged enrollment ratios is a stable one. The available data on school attainment in the labour 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. Furthermore, if the enrollment rates on which the projection method is based are measured with error, the coefficient estimates will be biased downward, yielding inconsistent predictions even if the stability assumption was correct.

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 labour force. It therefore includes adults who are not labour force participants and it may exclude some of the members of the labour 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 (2001) 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. 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 labour 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 takes place.[8]

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 labour 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 by the earnings return it generates in the labour 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:

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

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

$$W_s = W_0 \prod_{t=1}^{s} (1 + r_t). \tag{9$''$}$$

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

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

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

$$\ln W_s = \ln W_0 + rs. \tag{9}$$

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 labour studies has confirmed that this log-linear specification gives the best fit to the data (cf. Card, 1999; Krueger and Lindahl, 2001). 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 tth 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:

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

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 (2001), and Ciccone and Peri (2000) show that there is little evidence in favor of such external returns to education.[9]

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

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

where H^M is the stock of human capital based on the Mincer specification, L is labour as measured by the number of workers,[10] and $h \equiv H/L$ is the stock of human capital per worker. The function $\phi(s)$ reflects the efficiency of a unit of labour with s years of schooling relative to one with no schooling. With $\phi(s)=0$, the specification melts down to one with undifferentiated labour 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 labour literature, so that $\phi'(s)=r$. In the simplest specification, this would imply

$$\phi(s) = rs. \tag{12}$$

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 labour studies which weight each year of schooling by its market return.[11] 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 (1997), Hall and Jones (1999), and Jovanovic and Rob (1999).[12] 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 labour 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 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:

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

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.[13]

Barro and Lee (2001) 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 labour literature has shown at least for the United States 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 favour of externalities to education (see above).[14]

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 labour 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.

3.3.1 *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, 2003).

3.3.2 *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 labour markets are perfectly competitive, that labour 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

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

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 4.1). 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. Labour markets are not very competitive in many countries, given collective bargaining mechanisms and uniform wage setting. Labour 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.

3.3.3 *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.*, 2002). 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 labour force.[15]

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. Using the United States as the reference country seems warranted by the fact that the returns to schooling should be relatively undistorted on the competitive US labour market. 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. That is, the measure of quality-adjusted years of schooling Qs enters a Mincer-type equation with rates of return r.

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 labour 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 labour 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.

4. Comparison of Human Capital Measures

4.1. *Human Capital Data*

To be able to compare the different measures of human capital proposed in the literature, several data sources are exploited, using data for 1990 or the most recent year available. 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 (2001) 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 (2001). Years of schooling in the population aged 15 and over are taken because this age group corresponds better to the labour 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.* (2002) use

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

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).[16] 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 (2001).

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 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.[17]

4.2. *Comparison of the Different Human Capital Specifications*

Table 1 presents the measures of human capital stocks based on the different specifications. 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 based on the Summers and Heston (1991) data.[18]

The results in Table 1 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 cross-country comparison of the different specifications, Table 2 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 (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} range 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 (2001) 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.

In sum, there seem to be substantial differences between the different measures of the stock of human capital, and even between those measures which do not take into account differences in the quality of education. Given that the human capital specification which takes account of international differences in the educational quality is relatively weakly related to the other specifications, the recognition of international differences in the quality of education seems to introduce a substantial amount of additional information into the measure of human capital. The differences in the human capital measures may lead to largely different results in an empirical application of the different measures, and thus to diverging conclusions on the importance of human capital for economic growth.

Table 1. Data on Human Capital Specifications
Relative to the United States. Absolute U.S. values reported in the first row. (Countries ranked by output per worker.)

	[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	[12] Note: Q
United States (Abs.)	–	91.1	11.9	11.6	12.1	11.7	12.9	3.3	6.9	4.3	6.9	46.77
Luxembourg	–	–	0.420	–	0.571	–	–	0.820	0.662	0.708	0.615	0.951
United States	–	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	0.929*
United Arab E.	0.770	0.776	–	–	–	–	–	0.698	0.484	0.598	0.444	0.929*
Canada	–	1.093	0.891	0.862	0.826	0.936	0.991	0.950	0.898	0.864	1.216	1.167
Switzerland	–	0.783	0.403	0.599	–	0.864	0.971	0.897	0.804	0.819	1.370	1.312
Belgium	–	0.901	0.782	0.721	0.774	0.756	0.756	0.823	0.704	0.862	0.997	1.220
Netherlands	–	0.947	0.899	0.725	0.784	0.745	0.848	0.816	0.665	0.604	0.856	1.166
Italy	–	0.773	0.597	0.684	0.756	0.552	0.620	0.665	0.446	0.529	0.475	1.056
France	–	0.910	0.748	0.732	0.789	0.592	0.842	0.697	0.486	0.564	0.616	1.197
Australia	–	0.834	0.824	0.654	0.722	0.884	0.951	0.911	0.888	0.923	1.427	1.262
Germany, West	–	0.833	0.706	0.731	0.855	0.827	1.006	0.871	0.684	0.733	0.728	1.041
Bahamas	0.980	–	–	–	–	–	–	0.717	0.514	0.881	0.530	1.025*
Norway	–	0.899	0.840	0.817	0.764	0.985	0.794	0.988	1.052	0.862	2.231	1.380
Sweden	–	0.813	0.664	0.848	0.797	0.810	0.807	0.859	0.735	0.776	1.062	1.228
Finland	–	0.980	0.966	0.844	0.896	0.799	0.765	0.852	0.734	0.763	1.141	1.273
Oman	–	0.600	0.227	–	–	–	–	0.617	0.402	0.506	0.341	0.837*
United Kingdom	–	0.818	0.748	0.879	0.703	0.747	0.847	0.817	0.695	0.704	1.175	1.337
Austria	–	0.870	0.672	0.754	0.709	0.661	0.848	0.757	0.523	0.599	0.685	1.210
Spain	–	0.920	0.672	0.616	0.802	0.549	0.550	0.662	0.454	0.588	0.515	1.110
Puerto Rico	–	–	–	–	–	–	–	0.633	0.427	1.136	0.397	0.934*
Kuwait	0.760	–	0.807	–	0.572	0.510	–	0.633	0.372	0.490	0.229	0.481
New Zealand	–	0.877	1.000	0.762	0.767	0.958	0.938	0.967	1.049	1.345	2.468	1.434
Iceland	–	0.886	0.857	0.791	0.708	0.691	–	0.781	0.609	0.664	0.697	1.095
Denmark	–	0.894	0.899	0.787	0.571	0.816	0.847	0.863	0.751	0.775	1.270	1.321
Singapore	0.890	0.673	0.756	0.631	0.570	0.507	–	0.631	0.420	0.428	0.746	1.542
Ireland	–	0.886	0.958	1.083	0.731	0.748	0.729	0.818	0.669	0.712	0.748	1.073
Israel	–	0.839	0.798	0.620	0.830	0.798	–	0.851	0.781	0.840	1.029	1.164
Saudi Arabia	0.590	0.542	0.261	–	0.244	–	–	0.617	0.402	0.506	0.341	0.837*
Hong Kong	0.910	–	0.605	–	0.645	0.780	–	0.839	0.682	1.159	1.560	1.536
Japan	–	0.844	0.916	0.946	0.783	0.763	0.871	0.828	0.687	0.528	1.279	1.400
Bahrain	0.820	0.903	1.017	–	–	0.423	–	0.571	0.354	0.459	0.226	0.496
Trinidad & Tobago	0.970	0.761	0.739	–	0.489	0.610	–	0.713	0.517	0.661	0.512	0.993
Taiwan	–	–	–	–	0.386	0.679	–	0.774	0.581	1.301	0.771	1.204
Malta	–	0.827	0.597	–	0.565	–	–	0.737	0.567	0.655	0.766	1.222
Cyprus	–	0.796	0.689	0.660	–	0.742	–	0.814	0.662	0.445	0.651	0.989
Greece	–	0.845	0.664	0.753	0.695	0.681	0.613	0.775	0.605	0.654	0.686	1.088
Venezuela	0.900	0.772	0.588	0.569	0.571	0.422	–	0.570	0.357	0.615	0.308	0.836
Mexico	0.880	0.718	0.555	0.511	0.584	0.572	–	0.681	0.480	0.683	0.377	0.796
Portugal	–	0.785	0.487	0.493	0.539	0.418	0.497	0.567	0.342	0.436	0.327	0.945
Korea, Rep.	0.970	0.866	0.857	0.665	0.657	0.847	–	0.885	0.789	0.908	1.207	1.252
Syria	0.660	0.752	0.739	–	0.548	0.435	–	0.579	0.361	0.510	0.262	0.646
U.S.S.R. (Rus. Fed.)	–	0.923	–	–	–	–	–	0.737	0.567	0.749	0.713	1.168
Barbados	0.970	–	1.017	–	0.663	0.674	–	0.769	0.576	0.726	0.844	1.279
Argentina	0.960	–	0.420	0.652	0.664	0.693	–	0.782	0.638	0.450	0.674	1.037

(*continued*)

Table 1. *Continued.*

	[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}	[12] Note: Q
Bulgaria	–	0.801	–	–	–	–	–	0.691	0.509	0.682	0.526	1.026*
Jordan	0.820	0.598	0.908	0.424	0.618	0.506	–	0.630	0.407	0.568	0.369	0.904
Malaysia	0.800	0.645	0.613	0.534	0.474	0.514	–	0.636	0.430	0.661	0.512	1.161
Algeria	0.550	0.711	0.378	0.354	0.385	0.362	–	0.531	0.310	0.447	0.229	0.600
Iraq	0.520	–	0.622	0.360	0.377	0.278	–	0.469	0.262	0.365	0.206	0.588
Chile	0.940	–	0.647	0.618	0.576	0.593	–	0.698	0.515	0.438	0.284	0.529
Uruguay	0.970	0.847	0.588	0.679	0.634	0.604	–	0.707	0.507	0.775	0.587	1.118
Fiji	0.890	0.806	0.681	–	0.549	0.669	–	0.764	0.636	0.958	0.910	1.242
Iran	–	0.720	0.546	0.328	0.476	0.338	–	0.515	0.294	0.439	0.192	0.390
Belize	0.300	–	–	–	–	–	–	0.594	0.383	0.567	0.333	0.855*
Brazil	0.810	0.739	0.395	0.380	0.458	0.342	–	0.519	0.305	0.761	0.260	0.783
Hungary	–	0.743	–	–	–	0.761	–	0.826	0.764	0.818	1.276	1.309
Mauritius	0.800	0.645	0.613	–	0.522	0.474	–	0.607	0.396	0.692	0.472	1.175
Colombia	0.900	0.622	0.513	0.436	0.540	0.400	–	0.556	0.333	0.520	0.284	0.810
Costa Rica	0.940	0.684	0.588	–	0.681	0.473	–	0.606	0.394	0.448	0.389	0.987
Yugoslavia	–	–	–	–	–	0.601	–	0.705	0.541	0.291	0.662	1.154
South Africa	0.800	0.874	0.252	–	–	0.460	–	0.596	0.399	0.730	0.440	1.097
Namibia	–	–	–	–	–	–	–	0.520	0.305	0.519	0.270	0.834*
Seychelles	–	–	–	–	–	–	–	0.555	0.340	0.538	0.316	0.913*
Ecuador	0.870	0.772	0.605	0.493	0.725	0.503	–	0.627	0.413	0.529	0.347	0.834
Tunisia	0.600	0.677	0.361	0.415	0.468	0.335	–	0.513	0.296	0.429	0.269	0.866
Turkey	0.790	0.606	0.462	0.387	0.523	0.353	–	0.525	0.309	0.434	0.276	0.849
Gabon	0.560	–	0.218	–	0.663	–	–	0.555	0.340	0.538	0.316	0.913*
Yemen	–	–	0.050	–	–	0.126	–	0.370	0.191	0.266	0.179	0.758*
Panama	0.890	0.739	0.975	0.644	0.661	0.688	–	0.779	0.619	0.885	0.619	1.000
Czechoslovakia	–	0.787	–	–	–	–	–	0.737	0.567	0.655	0.654	1.105*
Suriname	0.920	–	0.681	–	0.503	–	–	0.633	0.427	0.564	0.397	0.934*
Poland	–	0.829	–	–	–	0.806	–	0.857	0.858	1.059	1.673	1.376
Guatemala	0.530	–	0.202	0.303	0.304	0.259	–	0.455	0.256	0.390	0.236	0.855*
Reunion	–	–	–	–	–	–	–	0.555	0.340	0.538	0.316	0.913*
Dominican Rep.	0.800	–	0.487	–	–	0.378	–	0.541	0.320	0.483	0.283	0.841
Egypt	0.480	0.737	0.588	0.412	0.471	0.363	–	0.532	0.307	0.483	0.222	0.565
Peru	0.860	0.854	0.672	0.565	0.657	0.529	–	0.647	0.434	0.641	0.381	0.880
Morocco	–	–	0.303	0.208	0.288	–	–	0.553	0.336	1.387	0.276	0.763*
Thailand	0.930	–	0.370	0.493	0.456	0.476	–	0.607	0.414	1.065	0.409	0.989
Solomon Is.	–	–	–	–	–	–	–	0.526	0.308	0.522	0.289	0.917*
Botswana	0.650	0.739	0.244	–	0.292	0.455	–	0.593	0.396	2.135	0.287	0.678
Western Samoa	–	–	–	–	–	–	–	0.591	0.377	0.583	0.361	0.954*
Grenada	–	–	–	–	–	–	–	0.594	0.383	0.567	0.333	0.855*
Paraguay	0.910	0.615	0.370	0.500	0.510	0.523	–	0.642	0.442	0.709	0.376	0.854
Swaziland	0.720	0.720	0.311	–	0.447	0.450	–	0.590	0.398	0.685	0.346	0.861
Dominica	–	–	–	–	0.550	–	–	0.594	0.383	0.567	0.333	0.855*
Tonga	–	–	–	–	–	–	–	0.591	0.377	0.583	0.361	0.954*
St. Vincent & Gre.	–	–	–	–	–	–	–	0.594	0.383	0.567	0.333	0.855*
Sri Lanka	0.890	0.728	0.697	0.540	0.499	0.517	–	0.638	0.421	0.728	0.382	0.910
El Salvador	0.690	0.620	0.328	0.428	0.349	0.362	–	0.531	0.324	0.454	0.228	0.560
St. Lucia	–	–	–	–	–	–	–	0.594	0.383	0.567	0.333	0.855*
Bolivia	0.790	0.693	0.412	0.544	0.444	0.428	–	0.574	0.364	0.368	0.249	0.587
Vanuatu	–	–	–	–	–	–	–	0.591	0.377	0.583	0.361	0.954*
Jamaica	0.830	0.697	0.941	0.693	0.488	0.404	–	0.558	0.336	0.457	0.347	1.040
Indonesia	0.820	0.673	0.345	0.381	0.370	0.341	–	0.518	0.302	0.494	0.285	0.919
Djibouti	0.410	0.215	–	–	–	–	–	0.520	0.305	0.519	0.270	0.834*

Bangladesh	0.350	0.381	0.269	0.269	0.288	0.187	–	0.407	0.217	0.358	0.210	0.917*
Philippines	0.940	0.847	0.891	0.667	0.734	0.620	–	0.721	0.532	0.562	0.369	0.717
Pakistan	0.340	0.339	0.252	0.182	0.210	0.353	–	0.525	0.293	0.369	0.276	0.917*
Congo	0.680	0.822	0.319	–	–	0.437	–	0.580	0.357	0.621	0.386	1.088
Honduras	0.690	–	0.311	0.383	0.467	0.358	–	0.528	0.317	0.508	0.235	0.611
Nicaragua	0.640	0.617	0.487	–	0.498	0.311	–	0.494	0.284	0.430	0.215	0.584
Romania	–	0.729	–	–	–	–	–	0.691	0.509	0.682	0.526	1.026*
Mongolia	0.800	0.719	–	–	–	–	–	0.591	0.377	0.583	0.361	0.954*
India	0.480	0.568	0.429	0.305	0.393	0.349	–	0.523	0.308	0.654	0.203	0.445
Cote d'Ivoire	0.340	–	0.193	0.181	0.340	–	–	0.520	0.305	0.519	0.270	0.834*
Papua New Guinea	0.680	–	0.126	–	0.232	0.196	–	0.412	0.226	0.319	0.180	0.483
Guyana	0.970	–	0.983	–	0.514	0.484	–	0.614	0.416	0.689	0.462	1.101
Laos	0.520	–	–	–	–	–	–	0.526	0.308	0.522	0.289	0.917*
Cape Verde Is.	0.630	0.605	–	–	–	–	–	0.520	0.305	0.519	0.270	0.834*
Cameroon	0.570	0.577	0.286	0.269	0.449	0.262	–	0.457	0.258	0.432	0.244	0.906
Sierra Leone	0.270	0.314	0.143	0.190	0.164	0.182	–	0.403	0.215	0.360	0.199	0.796*
Zimbabwe	0.820	0.754	0.370	0.389	0.402	0.429	–	0.575	0.356	0.726	0.311	0.848
Senegal	0.290	0.338	0.143	0.173	0.205	0.193	–	0.410	0.222	0.369	0.207	0.834*
Sudan	0.400	0.341	0.168	0.160	0.173	0.140	–	0.378	0.197	0.322	0.185	0.796*
Nepal	0.240	0.603	0.193	–	0.168	0.132	–	0.373	0.190	0.311	0.186	0.917*
China	0.780	0.587	–	0.448	–	0.498	–	0.624	0.416	0.722	0.618	1.377
Liberia	0.340	–	0.210	–	0.267	0.183	–	0.404	0.215	0.487	0.199	0.796*
Nigeria	0.490	–	0.210	0.210	0.166	–	–	0.447	0.249	0.426	0.228	0.832
Lesotho	0.670	0.665	0.168	–	0.404	0.334	–	0.512	0.312	0.366	0.339	1.111
Zambia	0.730	0.618	0.202	0.388	0.317	0.356	–	0.527	0.325	0.608	0.273	0.783
Haiti	0.410	–	0.160	0.226	0.220	0.248	–	0.447	0.249	0.406	0.226	0.817*
Benin	–	0.333	0.151	–	0.193	0.166	–	0.393	0.209	0.358	0.194	0.796*
Ghana	0.580	0.493	0.395	0.391	0.319	0.308	–	0.492	0.278	0.422	0.208	0.547
Kenya	0.720	0.637	0.202	0.356	0.285	0.311	–	0.494	0.292	0.518	0.227	0.636
Gambia	0.340	–	0.126	–	0.128	0.138	–	0.377	0.196	0.332	0.184	0.796*
Mauritania	0.350	0.285	0.084	0.573	0.085	0.206	–	0.419	0.230	0.402	0.209	0.796*
Somalia	–	–	0.092	–	0.068	–	–	0.447	0.249	0.398	0.224	0.796*
Guinea	0.310	0.211	–	–	–	–	–	0.447	0.249	0.444	0.224	0.796*
Togo	0.450	0.598	0.244	–	–	0.250	–	0.449	0.249	0.442	0.212	0.699
Madagascar	–	0.462	0.218	0.300	0.356	–	–	0.447	0.249	0.444	0.224	0.796*
Mozambique	0.350	–	0.059	0.226	0.174	0.077	–	0.342	0.174	0.288	0.162	0.597
Rwanda	0.540	–	0.034	0.239	0.268	0.179	–	0.401	0.220	0.381	0.202	0.796*
Bhutan	0.370	–	–	–	–	–	–	0.526	0.308	0.522	0.289	0.917*
Guinea-Biss.	0.500	–	–	–	0.190	0.055	–	0.330	0.165	0.270	0.161	0.796*
Angola	–	0.378	0.151	0.157	0.305	–	–	0.520	0.305	0.519	0.270	0.834*
Myanmar (Burma)	0.810	0.494	0.294	0.222	0.409	0.211	–	0.422	0.228	0.377	0.220	0.917*
Comoros	0.540	–	–	0.679	–	–	–	0.447	0.249	0.444	0.224	0.796*
Central Afr. R.	0.500	0.345	0.118	–	0.295	0.200	–	0.415	0.223	0.388	0.183	0.530
Malawi	0.520	0.436	0.050	0.293	0.163	0.231	–	0.436	0.248	0.348	0.222	0.796*
Chad	0.430	–	0.034	–	0.151	–	–	0.447	0.249	0.444	0.224	0.796*
Uganda	0.570	0.437	0.092	0.216	0.243	0.278	–	0.469	0.271	1.672	0.239	0.796*
Tanzania	0.620	0.371	0.042	0.216	0.152	0.237	–	0.440	0.251	0.439	0.225	0.796*
Zaire (Congo, D. R.)	0.720	–	0.303	0.344	0.358	0.239	–	0.441	0.246	0.436	0.212	0.717
Mali	0.250	0.151	0.084	0.097	0.119	0.057	–	0.331	0.165	0.271	0.161	0.796*
Burundi	0.310	0.348	0.034	–	0.143	0.118	–	0.364	0.190	0.321	0.180	0.796*
Burkina Faso	0.160	0.181	0.034	–	0.061	–	–	0.447	0.249	0.444	0.224	0.796*
Niger	0.120	0.159	0.042	–	0.069	0.070	–	0.338	0.170	0.280	0.165	0.796*
Ethiopia	0.310	0.206	0.092	0.049	0.094	–	–	0.447	0.249	0.415	0.224	0.796*

Notes: [1]l (column [1]): Absolute value of the adult literacy rate.
* Imputed Q data.

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

4.3. *Impact on the Results of Growth Research*

To show the importance of an improved specification of the stock of human capital in growth research, Table 3 reports results of development-accounting exercises for the human-capital specifications which are based on Mincerian human-capital theory. The development-accounting exercises, which look at sources of differences in levels of economic development across countries in 1990, use the covariance measure proposed by Klenow and Rodríguez-Clare (1997) to decompose the international variance in output per worker y into the relative contributions of differences in human capital stocks, in physical capital stocks, and in levels of total factor productivity in a simple neoclassical growth framework. The covariance measure calculates the respective average fraction of output dispersion across countries which can be statistically attributed to international differences in human capital stocks h and in physical capital-output ratios k/y, leaving the rest to be explained by residual total factor productivity A. Details on the development-accounting methodology and on the data on output and physical capital can be found in Wößmann (2002).

In the broadest sample of countries for which the output and physical-capital data is available ($n = 132$), differences in human capital per worker h^{HJ} account

Table 3. Development-Accounting Results

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
Human capital specification:				
$X = HJ$	0.21	0.19	0.60	132
$X = M$	0.33	0.19	0.48	132
$X = r$	0.18	0.19	0.63	132
$X = Q$	0.45	0.19	0.36	132
Different samples of countries:	h^Q			
Non-imputed s^{ATT} data	0.51	0.19	0.30	104
PWT benchmark study and non-imputed s^{ATT} and Q data	0.60	0.13	0.27	64
PWT benchmark, non-imputed s^{ATT} data, and non-projected Q data	0.61	0.13	0.26	29

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

for 21 percent of the international variation in output per worker when the stock of human capital is measures as in Hall and Jones (1999). Since another 19 percent can be attributed to differences in the physical capital-output ratio, 60 percent remain as differences in 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. This should reflect the substantial measurement errors in many of the country-specific estimates of rates of return, as well as the fact that there is certainly no world-wide competitive labour market.

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 fourth row of Table 3. The adjustment of the human capital specification for differences in the quality of schooling 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 empirical growth research. Furthermore, the empirical merits of different theories of economic growth and development may be severely misjudged when using misspecified measures of human capital.

Further results on the quality-adjusted human capital specification for different sub-samples of countries reveal that the share attributed to human capital seems to be additionally understated through the use of non-original human capital data. When countries with imputed values on years of schooling s^{ATT} are excluded ($n = 104$), the share of development variation accounted for by human capital exceeds 50 percent. In the sample which excludes countries which never participated in one of the benchmark studies underlying the Penn World Tables (PWT) and countries which have imputed s^{ATT} or Q data ($n = 64$), 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 29 countries which do not have any imputed or projected human capital data (s^{ATT} and Q) and which participated in a PWT benchmark study, similarly 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.

Likewise, in the sample of OECD countries, whose economies work under a relatively similar open institutional framework, the share of development variation accounted for by differences in human capital stocks increases from 39 percent with the h^{HJ} measure to 100 percent with the h^{Q} measure (for details, see Wößmann, 2002). 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 OECD development levels can be accounted for by differences in human capital once the human capital measure is adjusted for differences in the quality of schooling. Furthermore, Wößmann (2002) shows that the effect on development-accounting results of the specification error introduced by the use of inferior rate of return estimates and by the disregard of differences in educational quality is far greater than that of the recording errors in the data on educational quantity which have recently been stressed by Krueger and Lindahl (2001) and de la Fuente and Doménech (2000).

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. Two crucial aspects of human capital specification which can strongly influence the estimated growth effect of human capital are the correct inclusion of rates of return to education and the consideration of the quality of education. The development-accounting results show that the development impact of human capital seems to be severely understated by human capital specifications which neglect these specification issues. Using the quality-adjusted measure of human capital h^{Q}, cross-country differences in the stock of 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 – compared to less than a quarter and less than half, respectively, with human capital measured as h^{HJ}.

The preferred human capital specification h^Q presented in this paper is certainly not the last word in the academic quest for improvements in human capital measurement. The quality of the estimates of rates of return to education and of the measures of educational quality are without doubt limited, and the construction and method of inclusion of the quality weights employed in calculating h^Q is rather ad-hoc. Nevertheless, the quality-adjusted human capital specification based on a Mincer specification with decreasing returns to education constitutes a substantial advancement over the most commonly used proxy, average years of schooling, and the relevance of the adoption of the improvements is highlighted by the development-accounting results. In light of the gradual advancements in the specification of human capital surveyed in this review, it may be hoped that future improvements in the quality of the underlying data and in the specification of the human capital measure may further increase our knowledge of human capital issues.

While this paper has focussed on education as a means to accumulate human capital, an encompassing specification of human capital should also consider the whole range of other investments which people make to improve their productivity. In addition to formal education, these investments 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 the variable 'age minus pre-schooling years minus years of schooling' has been used as a proxy for experience and the variables 'life expectancy' and 'infant mortality rate' have been used as proxies 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. The abilities to read, communicate, and argue, to choose in a more informed way, or to be taken more seriously by others are among such additional benefits of education as valued by the broader human-capability perspective.

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Notes

1. For a history of the concept of human capital, see Kiker (1968). For a brief exposition of the history of human capital estimation, see Dagum and Slottje (2000), who include the highly problematic retrospective cost-of-production approach in addition to the prospective income-based approach and the proxy educational-stock approach which are dealt with in this paper.
2. 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.
3. See Pritchett (2001) 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.
4. For an application which uses data on levels of educational attainment directly, see Temple (2001a).
5. Note that the perpetual inventory formula given in Nehru *et al*. (1995) is erroneous.
6. Kyriacou (1991) does not give an explicit rationale for the lag structure chosen between years of schooling and enrollment rates, or specifically for choosing the same lag for the enrollment ratios at the secondary and higher level, but only reports that he heuristically found a strong relationship of the form of equation (6).
7. 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.
8. Additionally, using average years of schooling assumes perfect substitutability of workers across attainment levels and a constant elasticity of substitution across subgroups of workers at any time and place (Mulligan and Sala-i-Martin, 2000).
9. 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 (2001b) for a discussion of the issues involved.
10. Note that in this work, no adjustment is made for differences in hours worked, as the early growth accounting studies did (Section 2.1).
11. 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.

12. Jones (1996), Topel (1999) and Krueger and Lindahl (2001) also specify the relationship between income and years of schooling in a log-linear way.
13. 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).
14. Mulligan and Sala-i-Martin (1997) also suggest a measure of human capital based on labour income, namely the ratio of the average wage of the labour 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 labour 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 labour-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.
15. Hanushek and Kimko (2000) show that such quality measures of education matter more in growth regressions than quantity measures, a finding also confirmed by Barro (2001).
16. 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.
17. 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.
18. To allow for an evaluation of the quality component of the quality-adjusted human capital specification h^Q, column [12] of Table 1 reports Hanushek and Kimko's (2000) index of educational quality.

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