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Human Capital and Growth: Some Results for the OECD [1]

Abstract

This paper summarizes the results of a series of studies that construct new attainment series for a sample of OECD members and analyze the contribution of investment in human capital to productivity growth after correcting the bias generated by the existence of measurement error in the schooling data.

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1 Introduction

One of the most distinctive features of the "new" theories of growth has been the broadening of the relevant concept of capital. While traditional neoclassical models focused almost exclusively on the accumulation of physical capital (equipment and structures), more recent contributions have attributed increasing importance to the accumulation of human capital and productive knowledge and to the interaction between these two factors.

The empirical evidence, however, has not always been consistent with the new theoretical models. In the case of human capital, in particular, some recent studies have produced discouraging results. Educational variables are often not significant or even enter with the "wrong" sign in growth regressions, particularly when these are estimated using differenced specifications or panel techniques. The accumulation of negative results in the literature has generated a growing skepticism about the role of schooling in the growth process and has even led some authors (see in particular Pritchett, 2001) to seriously consider the reasons why educational investment may not contribute to productivity growth.

An alternative hypothesis that has received considerable attention by researchers in the area is that such negative results could be due, at least in part, to the poor quality of the schooling data that have been used in empirical studies of the determinants of growth. This article summarizes the main results of a series of papers that provide evidence in support of this hypothesis (de la Fuente and Doménech, 2000, 2001a, 2001b, 2002 and 2006). The paper is organized as follows. Sections 2 and 3 briefly survey the theoretical and empirical literature on growth and human capital and review the main educational data sets that have been used in this literature. Section 4 presents a new schooling series for a sample of 21 OECD countries that makes use of previously unexploited information. Section 5 discusses a series of indicators of the quality or information content of the existing schooling data sets that have been constructed using an extension of the technique proposed by Krueger

[1] *This article summarizes the results of a series of papers written in collaboration with R. Doménech. These studies have been financed by the European Fund for Regional Development, the OECD, Fundación Caixa Galicia and the Spanish Ministry of Science and Technology (through grants SEC99-1189 and SEC2002-01612).*

and Lindhal (2001). Different specifications of an aggregate production function are then estimated with each of these schooling series. Finally, the results of the last two exercises are used to correct the bias induced by measurement error. With this correction, the contribution of investment in human capital to productivity growth is positive and quite sizable.

2 Human Capital and Growth: Theoretical Framework and Empirical Evidence

Theoretical models of human capital and growth are built around the hypothesis that knowledge and skills embodied in humans directly raise productivity and increase an economy's ability to develop and to adopt new technologies. In order to explore its implications and open the way for its empirical testing, this basic hypothesis is generally formalized in one of two (not mutually exclusive) ways. The simplest one involves introducing the stock of human capital (which will be denoted by H throughout this paper) as an additional input in an otherwise standard production function linking aggregate output to the stocks of productive inputs (generally employment and physical capital) and to an index of technical efficiency or total factor productivity (TFP). The second possibility is to include H in the model as a determinant of the rate of technological progress (that is, the rate of growth of TFP). This involves specifying a technical progress function that may include as additional arguments variables related to R&D investment and the gap between each country and the world technological frontier.

In what follows, I will refer to the first of these links between human capital and productivity as *level effects* (because the stock of human capital has a direct impact on the level of output) and to the second one as *rate effects* (because H affects the growth rate of output through TFP). Box 1 develops a simple model of growth with human capital that formalizes the preceding discussion and incorporates both effects.

Some recent theoretical models also suggest that the accumulation of human capital may give rise to important externalities that would justify corrective public interventions. The problem arises because some of the benefits of a more educated labor force will typically "leak out" and generate benefits that cannot be appropriated in the form of higher earnings by those who undertake the relevant investment, thereby driving a wedge between the private and social returns to education. Lucas (1988), for example, suggests that the average stock of human capital at the economy-wide level increases productivity at the firm level holding the firm's own stock of human capital constant. It is also commonly assumed that the rate effects of human capital on technical progress include a large externality component because it is difficult to appropriate privately the full economic value of new ideas. Azariadis and Drazen (1990), and implicitly Lucas (1988) as well, stress that younger cohorts are likely to benefit from the knowledge and skills accumulated by their elders, thus generating potentially important intergenerational externalities that operate both at home and in school. The literature also suggests that human capital can

Box 1

A Descriptive Model of Human Capital and Growth

This box develops a simple model of growth and human capital that has two components: an aggregate production function and a technical progress function. The production function will be assumed to be of the Cobb-Douglas type:

(1) $y_{it} = A_{it} K_{it}{}^{\alpha k} H_{it}{}^{\alpha h} L_{it}{}^{\alpha l}$

where y_{it} denotes the aggregate output of country i at time t, L_{it} is the level of employment, K_{it} the stock of physical capital, H_{it} the average stock of human capital per worker, and αy_{it} an index of technical efficiency or total factor productivity (TFP) which summarizes the current state of the technology and, possibly, omitted factors such as geographical location, climate, institutions and endowments of natural resources. The coefficients α_i (with $i = k, h, l$) measure the elasticity of output with respect to the stocks of the different factors. An increase of 1% in the stock of human capital per worker, for instance, would increase output by α_h%, holding constant the stocks of the other factors and the level of technical efficiency.

Under the standard assumption that (1) displays constant returns to scale in capital, labor and total human capital, LH, (i.e. that $\alpha_k + \alpha_l = 1$) we can define a per capita production function that will relate average productivity to average schooling and to the stock of capital per worker. Letting $Q = Y/L$ denote output per worker, $Z = K/L$ the stock of capital per worker, and dividing both sides of (1) by total employment, L, we have:

(2) $Q = AZ^{\alpha k} H^{\alpha h}$

The technical progress function describes the determinants of the growth rate of total factor productivity. I will assume that country i's TFP level can be written in the form:

(3) $A_{it} = B_t X_{it}$

where B_t denotes the world "technological frontier" (i.e. the maximum attainable level of efficiency in production given the current state of scientific and technological knowledge) and $X_{it} = A_{it}/B_t$ the "technological gap" between country i and the world frontier. It will be assumed that B_t grows at a constant and exogenous rate, g, and that the growth rate of X_{it} is given by

(4) $\Delta x_{it} = \gamma_{io} - \lambda x_{it} + \gamma_{it} H_{it}$

where x_{it} is the log of X_{it} and γ_{io} a country fixed effect that helps control for omitted variables such as R&D investment. Notice that this specification incorporates a technological diffusion or catch-up effect. If $\lambda > 0$, countries that are closer to the technological frontier will experience lower rates of TFP growth. As a result, relative TFP levels will tend to stabilize and their steady-state values will be partly determined by the level of schooling.

generate more diffuse "civic" externalities, as an increase in the educational level of the population may help reduce crime rates or contribute to the development of more effective institutions.

2.1 Empirical Evidence

Empirical studies of the productivity effects of human capital (or more broadly, of the determinants of economic growth) have followed one of two alternative approaches. The first one involves the specification and estimation of an ad-hoc equation relating growth in total or per capita output to a set of variables that are thought to be relevant on the basis of informal theoretical considerations. The second approach is based on the estimation of a structural relation between the level of output or its growth rate and the relevant explanatory variables that is derived from an explicit theoretical model built around an aggregate production function and, possibly, a technical progress function of the type described in box 1.

This basic framework for the "structural" analysis of the determinants of growth can give rise to a large number of empirical specifications. The production function can be estimated directly with the relevant variables expressed in levels or in growth rates when reliable data are available for the stocks of all the relevant production inputs. Alternatively, its parameters can be recovered from other specifications *(convergence* and *steady state equations)* that are designed for estimation when only data on investment flows (rather than factor stocks) are available. These specifications can be derived from production functions by replacing factor stocks or their growth rates by convenient approximations constructed using observed investment rates.

A large number of empirical studies have analyzed the relationship between human capital and growth using the different specifications I have just outlined.[2] The results have been mixed: while earlier studies on the subject generally produced positive results, the conclusions of a second group of more recent studies have been rather discouraging, as many of these studies failed to detect a significant positive correlation between average schooling and the level of productivity.[3] The main difference between the two sets of studies has to do with the use of econometric techniques that implicitly assign different weights to the cross-section and time-series variation in the data. While the first group of studies relied on cross-section data (working with a single observation per country that describes average behavior over a period of several decades), studies in the second group have used several observations per country, taken over shorter periods, and have employed panel techniques or differenced specifications that basically eliminate the cross-section variation in the data before proceeding to the estimation.

Although the estimation techniques used in the more recent studies have the important advantage that they control for unobservable differences across countries, they also have some disadvantages. Perhaps the main one is that they are more sensitive to measurement error in the data as errors tend to be greater in the time-series than in the cross-section dimension because they tend to cancel out when we work with averages over long periods. This suggests, as I have already noted in the introduction, that a possible explanation of the negative results obtained in many recent studies has to do with the poor quality of the schooling data that have been used in the growth literature. As we will see in the next section, most of the international schooling databases contain large amounts of noise that can be traced back to various inconsistencies of the primary data used to construct them. The existence of this noise induces a downward bias in the estimation of the coefficients that measure the impact of human capital (that is, a tendency to underestimate their values) because it

2 *Section 3 of the Appendix of de la Fuente and Ciccone (2002) contains a detailed survey of this literature.*

3 *See in particular Landau (1983), Baumol et al. (1989), Barro (1991) and Mankiw, Romer and Weil (1992) within the first group of studies and Kyriacou (1991), Knight et al. (1993), Benhabib and Spiegel (1994), Pritchett (1999), Islam (1995) and Caselli et al. (1996) within the second.*

generates spurious variability in the stock of human capital that is not matched by proportional changes in the level of productivity.

3 International Schooling Data Bases: a Brief Survey and Some Problems

Most governments gather information on a number of educational indicators through population censuses, labor force surveys and specialized studies and surveys. Various international organizations collect these data and compile comparative statistics that provide easily accessible and (supposedly) homogeneous information for a large number of countries. The most comprehensive regular source of international educational statistics is UNESCO's *Statistical Yearbook*. This publication provides reasonably complete yearly time series on school enrollment rates by level of education for most countries in the world and contains some data on the educational attainment of the adult population, government expenditures on education, teacher/pupil ratios and other variables of interest.[4]

The UNESCO's enrollment series have been used in a large number of empirical studies of the link between education and productivity. In many cases this choice reflects the easy availability and broad coverage of these data rather than their theoretical suitability for the purpose of the study. Enrollment rates can probably be considered an acceptable, although imperfect, proxy for the flow of educational investment. On the other hand, this variable is not necessarily a good indicator of the existing stock of human capital since average educational attainment (which is often the more interesting variable from a theoretical point of view) responds to investment flows only gradually and with a very considerable lag.

In an attempt to remedy these shortcomings, a number of researchers have constructed data sets that attempt to measure directly the educational stock embodied in the population or labor force of large samples of countries during a period of several decades. These data sets have generally been constructed by combining the available data on attainment levels with the UNESCO enrollment figures to obtain series of average years of schooling and the educational composition of the population or labor force. The best known attempts in this line are the work of Kyriacou (1991), the different versions of the Barro and Lee data set (1993, 1996, 2000) and the series constructed by World Bank researchers (Lau, Jamison and Louat (1991), Lau, Bhalla and Louat (1991) and Nehru, Swanson and Dubey, 1995).

In de la Fuente and Doménech (2000 and 2002) we briefly review the methodology used in these studies and compare the different data sets with each other, focusing in particular on the OECD, where the quality of the available information

[4] *Other useful sources include the UN's Demographic Yearbook, which also reports educational attainment levels by age group and, in recent years, the OECD's Annual Report on education in its member countries (Education at a Glance), which contains a great deal of information about the inputs and outputs of the educational system.*

should in principle be better than in developing countries. The analysis of the different series reveals very significant discrepancies among them in terms of the relative positions of many countries and implausible estimates or time profiles for at least some of them. Although the various studies generally coincide when comparisons are made across broad regions (e.g. the OECD versus LDCs – least developd countries – in various geographical areas), the discrepancies are very important when we focus on the group of industrialized economies. Another cause for concern is that existing estimates often display extremely large changes in attainment levels over periods as short as five years (particularly at the secondary and tertiary levels).

To a large extent, these problems have their origin in the deficiencies of the underlying primary data. As Behraman and Rosenzweig (1994) have noted, there are good reasons to worry about the accuracy and consistency of UNESCO's data on both attainment levels and enrollment rates. Our analysis of the different schooling data sets confirms this diagnostic and suggests that many of the problems detected in these data can be traced back to shortcomings of the primary statistics, which do not seem to be consistent, across countries or over time, in their treatment of vocational and technical training and other courses of study, and reflect at times the number of people who have started a certain level of education and, at others, those who have completed it.

4 A New Schooling Series for a Sample of Industrial Countries

Concerns about poor data quality and its implications for empirical estimates of the growth effects of human capital have motivated some recent studies that attempt to improve the signal to noise ratio in the schooling series by exploiting additional sources of information and introducing various corrections. This section summarizes the results of one of these studies (de la Fuente and Doménech, 2001b)[5] that constructs new schooling series for a sample of 21 OECD countries.[6]

To construct these series we first collected all the information we could find on the distribution of the adult population by educational level in OECD countries. We used both international publications and national sources (census reports and surveys, statistical yearbooks and unpublished data supplied by national governments and by the OECD). Next, we tried to reconstruct a plausible time profile of attainment in each country, using all the available data and a bit of common sense. For those countries for which reasonably complete series are avail-

[5] *This study extends and updates the series constructed in de la Fuente and Doménech (2000) for the same sample. Among other improvements, the revised series incorporate unpublished information supplied by the OECD and the national statistical institutes of about a dozen member states in response to a petition for assistance that was channeled through the Statistics and Indicators Division of the OECD.*

[6] *A closely related paper, both in terms of its objectives and its methodology, is Cohen and Soto (2001). These authors construct a schooling data set for a much larger sample of countries using census and survey data from UNESCO, the OECD's in-house educational data base, and the websites of national statistical agencies, together with enrolment rates from UNESCO and other sources.*

Table 1

Availability of Primary Data

	Secondary attainment			University attainment		
	direct/total observation	first observation	last observation	direct/total observation	first observation	last observation
U.S.A.	24/24	1960	1995	24/24	1960	1995
Netherlands	12/24	1960	1995	12/24	1960	1995
Italy	**15/24**	**1961**	**1999**	**5/8**	**1960**	**1998**
Belgium	13/24	1961	1995	12/24	1960	1995
Spain	12/21	1960	1991	12/21	1960	1991
Greece	15/24	1961	1995	15/24	1961	1997
Portugal	12/21	1960	1991	8/21	1960	1991
France	12/21	1960	1989	12/21	1960	1990
Ireland	15/24	1961	1998	11/24	1961	1998
Sweden	9/24	1960	1995	9/24	1960	1995
Norway	15/24	1960	1998	9/24	1960	1998
Denmark	**9/24**	**1973**	**1994**	**12/24**	**1973**	**1994**
Finland	16/24	1960	1995	21/24	1970	1995
Japan	8/21	1960	1990	12/21	1960	1990
New Zealand	10/24	1965	1998	10/24	1965	1998
U.K.	6/21	1960	1993	10/21	1960	1991
Switzerland	15/24	1960	1995	15/24	1960	1995
Austria	11/24	1961	1995	7/24	1961	1995
Australia	11/24	1965	1997	11/24	1966	1997
West Germany	**11/24**	**1970**	**1995**	**17/24**	**1961**	**1995**
United Germany	6/6	1991	1995	6/6	1991	1995
Canada	15/24	1961	1996	21/24	1960	1996

Source: OECD, national sources.

able, we have relied primarily on national sources. For the rest, we start from the most plausible set of attainment estimates available around 1990 or 1995 (taken generally from OECD sources) and proceed backwards, trying to avoid unreasonable jumps in the series that can only reflect changes in classification criteria. In some cases, the construction of the series involved subjective judgments to choose among alternative census or survey estimates when several are available. At times, we have also reinterpreted some of the data from international compilations as referring to somewhat broader or narrower schooling categories than the reported one.[7] Missing data points lying between available census observations are filled in by simple linear interpolation. Missing observations prior to the first census observation are estimated, whenever possible, by backward extrapolations that make use of census information on attainment levels disaggregated by age group.

[7] *Clearly, the construction of our series involves a fair amount of guesswork. Our "methodology" looks decidedly less scientific than the apparently more systematic estimation procedures used by other authors starting from supposedly homogeneous data. However, even a cursory examination of the data shows that there is no such homogeneity. Hence, we have found it preferable to rely on judgment to try to piece together the available information in a coherent manner than to take for granted the accuracy of the primary data. The results do look more plausible than most existing series, at least in terms of their time profile and, as I will show below, perform rather well in terms of a statistical indicator of data quality.*

Data availability varies widely across countries. Table 1 shows the fraction of the reported data points that are correspond to "direct observations" (taken from census or survey reports) and the earliest and latest such observations available for secondary and higher attainment levels. The number of possible observations is typically either 21 or 24 for each level of schooling depending on whether the series ends in 1990 or 1995 (two sublevels and a total times seven or eight quinquennial observations). In the case of Italy, there seem to be no short higher education courses, so the number of possible observations at the university level drops to eight.

As can be seen in the table, for most of the countries in the sample we have enough primary information to reconstruct reasonable attainment series covering the whole sample period. The more problematic cases are higlighted using bold characters. In the case of Italy, the main problem is that much of the available information refers to the population over six years of age. For Denmark and Germany (at the secondary level), the earliest available direct observation refers to 1970 or later. In these two cases, we have projected attainment rates backward to 1960 using the attainment growth rates reported in OECD (1974), but we are unsure of the reliability of this extrapolation.

After estimating the breakdown of the adult population by educational level, we have calculated the average number of years of schooling taking into account the theoretical duration of the different school cycles in each country. The results are summarized in table 2. The last row of the table

Table 2

Average Years of Schooling of the Adult Population

Sample average = 100 in each year

	1960	1965	1970	1975	1980	1985	1990
West Germany	118.5	120.1	121.6	121.7	121.7	122.1	121.7
Australia	117.7	120.6	122.6	124.0	125.7	124.2	121.1
Canada	124.1	123.5	123.2	123.1	122.9	121.2	119.7
U.S.A.	126.3	126.1	125.4	124.5	123.1	121.0	119.1
Switzerland	124.8	124.2	123.6	120.5	117.8	116.1	114.9
New Zealand	125.1	123.4	121.7	119.6	117.5	115.4	113.8
Denmark	129.0	125.9	123.0	119.8	116.9	113.7	110.2
Austria	**107.7**	**105.4**	**103.5**	**103.2**	**104.1**	**105.9**	**106.3**
Japan	103.1	103.3	103.5	104.8	105.6	105.5	105.6
Norway	115.8	113.6	111.6	108.9	107.1	106.1	104.4
Finland	91.5	94.5	96.8	98.6	100.7	102.0	103.1
Netherlands	97.0	97.6	98.1	99.0	100.1	101.4	102.9
Sweden	96.2	95.5	95.0	96.1	97.2	98.4	99.8
U.K.	102.5	101.7	100.8	99.9	99.0	98.8	98.9
France	97.3	98.6	100.2	101.3	99.9	98.9	98.2
Belgium	92.5	93.3	94.1	94.4	94.8	94.7	94.7
Ireland	88.0	86.8	86.9	86.5	86.0	87.0	88.4
Italy	64.7	66.7	68.6	69.6	70.7	73.1	75.6
Greece	66.5	67.5	68.5	70.1	71.8	73.1	74.3
Spain	59.5	58.5	57.5	58.5	59.5	62.8	66.7
Portugal	52.3	53.2	54.0	56.0	58.0	59.0	60.2
Average (in years)	8.36	8.69	9.02	9.45	9.87	10.28	10.64

Source: Author's calculations.

shows the (unweighted) average years of schooling for the entire sample. This variable increases by 27.3% between 1960 and 1990 as a result of the important improvement in the educational level of the younger cohorts observed in practically all countries. The rest of the rows show the position of the different countries relative to the sample average in each period, which is normalized to 100, with the countries arranged in decreasing order by school attainment in 1990.

5 Attenuation Bias and a Quality Indicator for the Most Commonly Used Schooling Series

Measurement error generates a tendency to underestimate the impact of human capital on productivity. Box 2 discusses the origin of this *attenuation bias* and describes a technique that can be used to construct an indicator of the quality of different series that measure with error a common underlying variable. Intuitively, the bias arises because measurement error introduces "noise" that tends to hide the relationship between the variables of interest. The quality indicator, known as the *reliability ratio*, measures the importance of such noise relative to the true signal contained in each of the series and is constructed on the basis of an analysis of the capacity of each series to explain the behaviour of the rest. This ratio is very useful, first because it provides an indicator of the informational content of each series, and second because the error in the estimation will be inversely proportional to its value. As a result, the reliability ratio can be used to correct the attenuation bias so as to obtain consistent estimators of the parameter of interest (i.e. estimators that are not biased in large samples).

In de la Fuente and Doménech (2002 and 2006) we use the procedure described in box 2 to construct an indicator of the information content of the series of years of schooling most commonly used in the growth literature, restricting ourselves to the sample of 21 OECD countries covered by the data set described in the previous section. This indicator is constructed for several transformations of the series of average years of schooling after removing period means from all the series so as to eliminate fixed time effects. In particular, we estimate reliability ratios for years of schooling measured in levels (S_{it}) and in logs (s_{it}), for average annual changes in both levels and logs measured across successive quinquennial observations (ΔS_{it} and Δs_{it}), and for log years of schooling measured in deviations from their country means ($s_{it} - s_i$). Notice that Δs_{it} corresponds to annual growth rates and $s_{it} - s_i$ is the "within" transformation often used to remove fixed effects.

The results are shown in table 3 with the different data sets arranged by decreasing average reliability ratios. The last row of the table shows the average value of the reliability ratio for each type of data transformation (taken across data sets), and the last column displays the average reliability ratio of each data set (taken across transformations). Our mean estimate of the reliability ratio for all the series and transformations is 0.335. Since this variable must lie between zero and one (with zero indicating that the series contains only noise and one that it is measured

Box 2

Attenuation Bias and the Reliability Ratio

The origin of the attenuation bias is the following one. Assume that the level of productivity, Q, is a linear function of the stock of human capital, H, given by

$$(1)\ Q = bH + u$$

where u is a random disturbance. Given this relationship, variations in the stock of human capital, H, will induce changes in Q, and the relative magnitude of the variations in these two variables will allow us to estimate the value of the coefficient b. Now, if H is measured with error, that is, if what we observe is not H itself but a noisy proxy for it, $P = H + \varepsilon$, where ε is a random measurement error, then part of the apparent variation in the stock of human capital (over time and across countries) will be due to measurement error – that is, it will be noise rather than true signal. Since such variations logically do not induce any response in Q, this variable will appear to be less sensible to H than it really is, thereby biasing toward zero the estimated value of b.

The size of the bias will be inversely related to the information content of the series, as measured by its reliability ratio, r. This variable is defined as the ratio between the signal and the sum of signal and noise contained in the data, that is,

$$(2)\ r \equiv \frac{var\ H}{var\ P} = \frac{var\ H}{var\ H + var\ \varepsilon}$$

where $var\ H$ measures the signal contained in the series and var ε the noise that distorts it.[1]

When several noisy proxies are available for a given variable, their respective reliability ratios can be estimated using a procedure proposed by Krueger and Lindhal (2001). Let $P_1 = H + \varepsilon_1$ and $P_2 = H + \varepsilon_2$ be two alternative proxies for the stock of human capital, H. It is easy to check that if the error terms of the two series, ε_1 and ε_2, are not correlated with each other, then the covariance between P_1 and P_2 can be used to estimate the variance of H, which is the only unknown magnitude in equation (2). It follows that, under this assumption, r_1 can be estimated as

$$(3)\ \hat{r}_1 = \frac{cov\ (P_1, P_2)}{var\ P_1}$$

which turns out to be the formula for the OLS estimator of the slope coefficient of a regression of P_2 on P_1. Hence, to estimate the reliability of P_1 we run a regression of the form $P_2 = c + r_1 P_1$.[2] *Notice, however, that if the measurement errors of the two series are positively correlated ($E\varepsilon_1 \varepsilon_2 > 0$) as may be expected in many cases, $\hat{r}_1$ will overestimate the reliability ratio and hence understate the extent of the attenuation bias induced by measurement error.*

In de la Fuente and Doménech (2002) we develop an extension of this procedure that can be used to construct a minimum-variance estimator of the reliability ratio whenever more than two noisy proxies are available for the same underlying variable, under the maintained assumption that measurement errors are uncorrelated across data sets. As in Krueger and Lindahl, the reliability ratio r_k of a given series of average years of schooling (say S_k) is estimated by using S_k to try to explain alternative estimates of the same variable (S_j with $j \neq k$). The main difference is that, rather than running a set of independent pairwise regressions with different data sets, the efficient estimator of the reliability ratio for data set j can be obtained as the slope coefficient of a restricted SUR model of the form

$$(4)\ P_k = c_k + r_j P_j + u_k \quad \text{for } k = 1..., K$$

[1] *Notice that the denominator of the last expression given in (2) implicitly assumes that the measurement error term, ε, is not correlated with H.*

[2] *Intuitively, regressing P_2 on P_1 gives us an idea of how well P_1 explains the true variable H because measurement error in the dependent variable (P_2 in this case) will be absorbed by the disturbance without generating any biases. Hence, it is almost as if we were regressing the true variable on P_1.*

where k denotes the "reference" data set and varies over the last available version of all data sets different from j. The reliability ratio of Barro and Lee's (2000) data set, for instance, is estimated by using these authors' estimate of average years of schooling as the explanatory variable in a set of regressions where the reference (dependent) variables are the average years of schooling estimated by Kyriacou (1991), Nehru et al. (1995), Cohen and Soto (2001) and ourselves. Other versions of the Barro and Lee data set, however, are not used as a reference because the correlation of measurement errors across the same family of schooling series is almost certainly very high and this will artificially inflate the estimated reliability ratio.

Table 3

SUR Estimates of Reliability Ratios, OECD Sample

Sample average = 100 in each year

	S_{it}	s_{it}	ΔS_{it}	Δs_{it}	s_{it}-s_i	Δs_{it}-Δs_i	Average
D&D (2002)	0.754	0.775	0.337	0.769	0.917	0.246	0.633
C&S (2001)	0.806	0.912	0.330	0.467	0.547	0.185	0.541
D&D (2000)	0.720	0.761	0.100	0.550	0.818	0.074	0.504
Kyr. (1991)	0.723	0.600	0.024	0.065	0.111	0.026	0.258
B&L (2000)	0.707	0.603	−0.018	0.045	0.178	−0.016	0.250
B&L (1996)	0.559	0.516	−0.017	0.039	0.146	−0.007	0.206
B&L (1993)	0.526	0.436	−0.019	0.029	0.121	−0.017	0.179
NSD (1995)	0.278	0.330	−0.021	0.066	0.095	−0.115	0.106
Average	0.634	0.617	0.090	0.254	0.367	0.047	0.335

Notes: All series are measured in deviations from their respective sample means in each period prior to estimation.
Key: D&D = de la Fuente and Doménech; C&S = Cohen and Soto; Kyr = Kyriacou; B&L = Barro and Lee; NSD = Nehru, Swanson and Dubey.

without error)[8] this result suggests that the average estimate of the coefficient of schooling in a growth equation is likely to suffer from a substantial downward bias, even without taking into account the further loss of signal that arises when additional regressors are included in these equations (see de la Fuente and Doménech, 2006). The bias will be smaller when the data are used in levels or logs, but is likely to be very large in fixed effects or differenced specifications. The average reliability ratio is only 0.254 for the data in quinquennial log differences, and 0.090 for level differences taken at the same frequency.

Our results indicate that the importance of measurement error varies significantly across data sets, although their precise ranking depends on the data transformation that is chosen. Two of the datasets most widely used in cross-country empirical work, those by Kyriacou (1991) and Barro and Lee (various years), perform relatively well when the data are used in levels but, as Krueger and Lindhal (2001) note, contain very little signal when the data are differenced. Recent efforts to increase the signal content of the schooling data seem to have been at least partially successful, although the attenuation bias continues to be potentially large

[8] *This is true as long as the measurement error terms of the different series are uncorrelated with each other and with H. As can be seen in table 3, some of our estimates of the reliability ratio lie outside this interval, which implies some violation of this assumption. In de la Fuente and Doménech (2002) we construct alternative estimates of reliability ratios under more general assumptions and find that the required corrections do not qualitatively change the results.*

even in these cases. Taking as a reference the average reliability ratio for the (1996) version of the Barro and Lee data set (0.206), the latest revision of these series by the same authors has increased their information content by 21%, while the estimates reported in Cohen and Soto (2001) and in de la Fuente and Doménech (2001) raise the estimated reliability ratio by 162% and 207% respectively.

6 Data Quality and Estimates of the Growth Effects of Human Capital

As we have seen in the previous section, the expected value of the attenuation bias is a decreasing function of the reliability ratio of the series used in the estimation. This suggests that the estimated value of the coefficient of human capital in a growth regression should increase with the quality of the schooling data. In de la Fuente and Doménech (2006) we show that this is indeed the case. We estimate various specifications of an aggregate production function using the different schooling series analyzed in the previous section as alternative proxies for the stock of human capital. We find that both the size and the significance of the coefficient of schooling increase as expected with the reliability ratio. Finally, we exploit this correlation to construct a set of "meta-estimates" of the parameter of interest that correct for measurement error bias.[9]

6.1 Results with Different Schooling Series

The equations we estimate are derived from a Cobb-Douglas aggregate production function with constant returns to scale that includes as inputs the stock of physical capital, the level of employment and the average level of education of the adult population. This equation is estimated in levels (with the variables measured in logarithms), in levels with fixed country effects and in first differences. We also estimate a fourth specification in differences that includes fixed country effects and incorporates a process of technological diffusion or catch-up. In this specification, the rate of growth of TFP is directly proportional to the technological distance between each country and the U.S.A., and the fixed country effects capture permanent differences in TFP levels that will presumably reflect differences in R&D expenditure and other omitted variables.[10]

These specifications are estimated using quinquennial data for our usual OECD sample that cover the period 1960–1990. All equations include fixed period effects (dummy variables for the different sample subperiods). The estimates of the coefficient that measures the elasticity of output with respect to the level of schooling (α_s)

[9] *A meta-estimate is an estimate that is not obtained directly from the data but is constructed using other primary estimates.*

[10] *All specifications are derived from equation (2) in box 1 using average years of schooling (S) as a proxy for the stock of human capital (H). The last specification also incorporates a technical progress function similar to equation (5) in the same box, except in that the stock of human capital is omitted. Hence, the estimated model does not allow for rate effects. We have tried to incorporate them but the results are not satisfactory. This problem arises frequently in the literature. See de la Fuente and Ciccone (2002) for a discussion of the reasons why it may be difficult to separate the rate and level effects of human capital.*

Table 4

Alternative Estimates of the Human Capital Coefficient (α_s) – Using Different Specifications and Schooling Series

	NSD	KYR	B&L (1993)	B&L (1996)	B&L (2000)	C&S	D&D (2000)	D&D (2002)	Average
Levels	0.078	0.186	0.141	0.165	0.238	0.397	0.407	0.378	0.249
	(2.02)	(2.18)	(4.49)	(4.82)	(6.19)	(7.98)	(7.76)	(6.92)	(5.30)
Fixed effects	0.068	0.066	0.136	0.115	0.203	0.608	0.627	0.958	0.348
	(0.76)	(1.86)	(3.30)	(1.80)	(3.74)	(4.49)	(3.99)	(6.51)	(3.31)
Differences	0.079	0.009	0.089	0.083	0.079	0.525	0.520	0.744	0.266
	(0.70)	(0.15)	(2.52)	(1.47)	(1.28)	(2.57)	(2.17)	(3.10)	(1.75)
Catch-up	– 0.206	0.014	0.056	−0.007	−0.019	0.573	0.587	0.540	0.192
	(1.61)	(0.29)	(1.80)	(0.11)	(0.31)	(3.52)	(3.47)	(2.89)	(1.24)
Average	0.005	0.069	0.106	0.089	0.125	0.526	0.535	0.655	
	(0.47)	(1.12)	(3.03)	(2.00)	(2.73)	(4.64)	(4.35)	(4.86)	

Key: See table 3.

obtained with the different specifications and schooling series are shown in Table 4. The last two rows of the table show average coefficient values and *t* ratios for each data set computed across the different specifications, and the last column reports the average values of α_s and the corresponding *t* statistic computed across data sets for each specification.

The pattern of results that emerges as we change the source of the human capital data is consistent with our hypothesis about the importance of educational data quality for growth estimates. For all the data sets, the estimated value of α_s is positive and significant in the specification in levels without fixed country effects (first set of rows in the table), but the size and significance of the estimates increases appreciably as we move to the data sets with higher reliability ratios (that correspond to the last columns of the table). The differences are even sharper when the estimation is repeated with fixed country effects (second set of rows) or with the data in growth rates with or without a catch-up effect (third and fourth blocks). The results obtained with the Kyriacou, Barro and Lee and Nehru et al. data in growth rates are consistent with those reported by Kyriacou (1991), Benhabib and Spiegel (1994) and Pritchett (1999), who find insignificant (and sometimes negative) coefficients for human capital in an aggregate production function estimated with differenced data. On the other hand, our series and those of Cohen and Soto produce rather large and precise estimates of the human capital coefficient in most equations and, in the case of our preferred catch-up specification, yield plausible values of the remaining parameters of the model as well, with estimates of α_k close to the share of physical capital in national income and positive diffusion coefficients.

6.2 Correcting for Measurement Error Bias

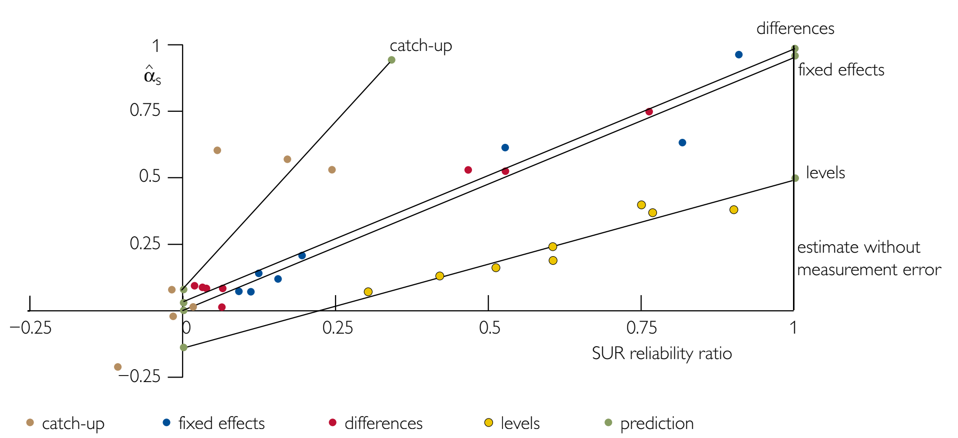
The results summarized in table 4 strongly suggest that measurement error induces a large downward bias in human capital coefficients. They also show that improvements in data quality reduce this bias and generate results that are generally more favourable to the view that investment in schooling contributes substantially to productivity growth. To make this point visually, the chart plots the various estimates of α_s given in table 4 against the corresponding SUR reliability ratios (taken from table 3), along with the regression lines that summarize the relationship between these two variables for each of the specifications estimated in the previous section. The scatter shows a clear positive correlation between OLS estimates and reliability ratios within each specification and suggests that the true value of α_s is at least 0.50 (which is the prediction of the levels equation for $r = 1$).

A the chart suggests, it is possible to extrapolate the relationship between the reliability ratio and the estimated human capital coefficient that is observed across data sets to estimate the value of α_s that would be obtained in the absence of measurement error. In this manner, it is possible to construct meta-estimates of this parameter that will be free of attenuation bias, although this has to be done a bit more carefully than the chart suggests when the growth equation includes additional regressors. In de la Fuente and Doménech (2002) we use a procedure of this type to obtain consistent meta-estimates of α_s. Working with the three linear specifications estimated above (that is, with all of them except for the catch-up model) and with different assumptions about the nature of measurement error (and in particular about its correlation across data sets and with the remaining explanatory variables in the model), we obtain nine different estimates of α_s that range from 0.587 to 2.606 with an average value of 1.11.

These values are significantly higher than those obtained in the previous literature. The smallest of them is roughly twice as large as Mankiw, Romer and Weil's (1992) estimate of 1/3, which could probably have been considered a consensus value for this parameter in the early 1990s and came then to be seen as too optimistic in the light of negative results in the literature. Our estimates, by contrast, point to a considerably higher

Chart 1

Estimated α_s vs. SUR Reliability Ratio



Source: Author's calculations.

figure and suggest that investment in human capital is an important growth factor whose effects have been underestimated in previous studies as a result of the poor quality of schooling data.

7 Conclusion

Existing data on educational attainment contain a considerable amount of noise that reflects various deficiencies of the primary data. In an attempt to increase the signal-to-noise ratio in these data, we have constructed new schooling series for a sample of OECD countries using previously unexploited information and an ad-hoc procedure that attempts to minimize the error generated by changes in classification criteria. We have also constructed a statistical measure of the information content of the schooling data sets used in the growth literature. This indicator supports our view that the amount of measurement error in these data is rather large, and suggests that both our attainment series and those constructed by Cohen and Soto (2001) constitute a significant improvement over earlier sources.

The studies summarized in this paper were originally motivated by the view that weak data is likely to be one of the main reasons for the discouraging results obtained in the empirical literature on human capital and growth. Our results clearly support this hypothesis, as does recent work by Krueger and Lindhal (2001) and Cohen and Soto (2001), and suggest that the contribution of investment in education to productivity growth is sizable. Unlike several older data sets, our revised series produce positive and theoretically plausible results using a variety of growth specifications. More importantly, our analysis of the performance of different schooling data sets in a variety of production function specifications shows a clear tendency for human capital coefficients to rise and become more precise as the information content of the schooling data increases. We have extrapolated this relationship to construct estimates of the value of the coefficient that would be obtained with the correctly measured stock of human capital. The exercise suggests that the true value of the elasticity of output with respect to the stock of human capital is almost certainly above 0.50, that is, at least 50% higher than the most optimistic estimate of reference in the previous literature.

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