ELSEVIER Journal of Monetary Economics 34 (1994) 143–173

JOURNAL OF Monetary ECONOMICS

The role of human capital in economic development Evidence from aggregate cross-country data

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(Received March 1993; final version received May 1994)

Abstract

Using cross-country estimates of physical and human capital stocks, we run the growth accounting regressions implied by a Cobb–Douglas aggregate production function. Our results indicate that human capital enters insignificantly in explaining per capita growth rates. We next specify an alternative model in which the growth rate of total factor productivity depends on a nation's human capital stock level. Tests of this specification do indicate a positive role for human capital.

Key words: Growth; Human capital

JEL classification: N10; N30

1. Introduction

How does human capital or the educational attainment of the labor force affect the output and the growth of an economy? A standard approach is to treat human capital, or the average years of schooling of the labor force, as an ordinary input in the production function. The recent work of Mankiw, Romer, and Weil (1992) is in this tradition. An alternative approach, associated with

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Technical assistance from the C.V. Starr Center for Applied Economics is gratefully acknowledged. Helpful comments were received from Boyan Jovanovic, Ross Levine, Franco Peracchi, Ned Phelps, Paul Romer, David Weil, seminar participants at the NBER growth workshop, and an anonymous referee.

0304-3932/94/$07.00
SSDI 0304393294011 54 X

endogenous growth theory,[1] is to model technological progress, or the growth of total factor productivity, as a function of the level of education or human capital. The presumption is that an educated labor force is better at creating, implementing, and adopting new technologies, thereby generating growth. In this paper, we attempt to empirically distinguish between these two approaches. At the end we also briefly comment on the impact of some ancillary variables, such as political instability and income inequality, on economic growth and factor accumulation.

Because of data constraints, the literature has often attempted to proxy the variables relevant to growth accounting by those which are directly observable. For example, although physical capital stocks are necessary to estimate the growth accounting equations, the literature has usually used gross investment rates as a proxy for physical capital accumulation (Barro, 1991).[2] In addition, human capital has been proxied in the literature by enrollment ratios or literacy rates. At best, however, enrollment ratios represent investment levels in human capital. Literacy is a stock variable, but there are important empirical problems associated with the use of literacy as a proxy for human capital.[3]

This paper uses estimates of physical and human capital stocks to examine cross-country evidence on the determinants of economic growth. We begin with estimation of a standard Cobb–Douglas production function in which labor and human and physical capital enter as factors of production. Our findings shed some doubt on the traditional role given to human capital in the development process as a separate factor of production. In our first set of results, we find that human capital growth has an insignificant, and usually negative effect in explaining per capita income growth. This result is robust to a number of alternative specifications and data sources, as well as to the possibility of bias which is encountered when regressing per capita income growth on accumulated factors of production.

Nonetheless, human capital accumulation has long been stressed as a prerequisite for economic growth. As pointed out by Nelson and Phelps (1966), by treating human capital simply as another factor in growth accounting we may be misspecifying its role. Below, we introduce an alternative model which allows human capital levels to directly affect aggregate factor productivity through two channels: Following Romer (1990a), we postulate that human capital may

[1]For example, see Romer (1990a, b).

[2]An exception is the work of Mankiw, Romer, and Weil (1992). In their study, they are able to generate a specification in terms of investment rates by assuming that all countries are in their steady state.

[3]These include quality of measurement differences across countries, biases introduced by the skewness of sampling towards urban areas, and the fact developed countries typically have literacy rates which are close to unity.

directly influence productivity by determining the capacity of nations to innovate new technologies suited to domestic production. Furthermore, we adapt the Nelson and Phelps (1966) model to allow human capital levels to affect the speed of technological catch-up and diffusion. We assume that the ability of a nation to adopt and implement new technology from abroad is a function of its domestic human capital stock. In our model, at every point in time there exists some country which is the world leader in technology. The speed with which nations 'catch up' to this leader country is then a function of their human capital stocks.

The combination of these two forces, domestic innovation and catch-up, produces some noteworthy results: First, under certain conditions (in particular when the innovation parameter dominates), growth rates may differ across countries for a long time due to differences in levels of human capital stocks. Second, a country which lies below the 'leader nation' in technology, but possesses a higher human capital stock, will catch up and overtake the leader in a finite time period. Third, the country with the highest stock of human capital will always eventually emerge as the technological leader nation in finite time and maintain its leadership as long as its human capital advantage is sustained.

We test the specification indicated by this alternative model below. Our findings assign a positive role to the levels of human capital in growth accounting. Our results below generally confirm that per capita income growth indeed depends positively upon average levels of human capital, although not always measurably at a 5% confidence level.

An additional role for human capital may be as an engine for attracting other factors, such as physical capital, which also contributes measurably to per capita income growth. Lucas (1990) suggested that physical capital fails to flow to poor countries because of their relatively poor endowments of complementary human capital. Below, we investigate this relationship by examining the determinants of cross-sectional gross investment rates as a share of the capital stock. In addition, we examine the implications of 'ancillary variables', including political instability and income distribution for investment rates.[4] Our results indicate that levels of human capital play an important role in attracting physical capital. However the ancillary variables fail to measurably affect rate of investment once one accounts for differences in factor accumulation across countries.

This paper is organized into seven sections. The following section introduces the methodology used in the standard growth accounting regressions and provides an overview of the generation of the physical and human capital stock variables. Section 3 then introduces the alternative theoretical model in which human capital plays a role in determining productivity, rather than entering on

[4]Other ancillary variables have been found to be significantly correlated with growth. For example, King and Levine (1992, 1993) find a strong correlation between financial development and growth.

its own as a factor of production. Section 4 empirically tests this alternative specification, including the robustness of the results to the inclusion of the ancillary variables. Section 5 then derives and tests a more structural specification. Section 6 investigates the impact of human capital on rates of physical capital accumulation. Section 7 concludes.

2. Growth accounting with human capital as a factor of production

2.1. Methodology and data

The standard growth accounting methodology with human capital specifies an aggregate production function in which per capita income, Y_t, is dependent upon three input factors – labor, L_t, physical capital, K_t, and human capital, H_t. Assuming a Cobb–Douglas technology, $Y_t = A_t K_t^{\alpha} L_t^{\beta} H_t^{\gamma} \varepsilon_t$, and taking log differences, the relationship for long-term growth can be expressed as

$$\begin{aligned}(\log Y_T - \log Y_0) = {} & (\log A_T - \log A_0) + \alpha(\log K_T - \log K_0) \\ & + \beta(\log L_T - \log L_0) + \gamma(\log H_T - \log H_0) \\ & + (\log \varepsilon_T - \log \varepsilon_0). \qquad (1)\end{aligned}$$

A difficulty associated with estimating aggregate production functions such as Eq. (1) concerns the possibility that because physical and human capital are accumulated factors, they will be correlated with the error term ε_t. This would imply the possibility of biased estimates. In the appendix, we attempt to empirically assess the likely signs of the biases on the coefficient estimates. Our results indicate that there is likely to be an upward coefficient bias on the α and γ estimates, and a downward bias on our estimate of β. In particular, this bias may lead us to overestimate the importance of human and physical capital accumulation in the growth equations.

We estimate Eq. (1) in the standard growth accounting framework by regressing log differences in income on log differences of factors. If this specification is correct, this methodology would provide estimates of the magnitudes of α, β, and γ. In addition, we introduce a number of 'ancillary variables' to allow for some productivity differences, such as proxies for political instability and distortionary activity.

In practice, data for physical and human capital stocks are not available for large cross-country samples. Nevertheless, we estimate a variety of measures of physical capital stocks of nations by using alternative assumptions to generate capital stock estimates from investment flows. Our results do not depend upon our choice of capital stock estimate. The various methodologies used in the construction of the capital stock estimates are described in the Appendix. Human capital stock estimates have been constructed by Kyriacou (1991).

Kyriacou estimates human capital stocks by first estimating the relationship between the educational attainment of the labor force from 1974 through 1977, available for 42 countries, and past values of human capital investment, such as enrollment in primary, secondary, and tertiary education. He then extrapolates from these results to a larger set of countries. His methodology is also described in greater detail in the appendix.

Income, population, and labor force data data are acquired from the Summers–Heston (1991) data set. Although one would expect that the labor force estimate would be a superior measure of the labor force of a country, we would suspect that the accuracy of this measure would vary broadly, and in particular be relatively suspect in less developed countries, where workers in traditional agriculture may or may not be recorded as members of the labor force. As a sensitivity measure, we run all regressions reported below using both population and labor force data. The results with population growth were quite similar to those obtained using labor force data.[5]

2.2. *Results*

Prior to running the formal growth regressions, one can see that the standard specification is unlikely to yield results which imply a strong role for human capital growth by observing the univariate relationship between log differences in income and the log differences in the factors of production. These are shown for the 1965 through 1985 period in Fig. 1. While log differences in physical capital and physical labor are shown to be positively correlated with log differences in income, the correlation with log differences in human capital is very close to zero. In addition, this result is not dependent upon our use of the Kyriacou (1991) measure of human capital. Fig. 2 shows that an equally weak correlation exists between log differences in income and log differences in either the Barro and Lee (1993) estimate of human capital or literacy.

The results for the growth regressions run on log differences in income from 1965 to 1985 are similar. See Table 1. Regressions were run using ordinary least squares with White's heteroscedasticity-consistent covariance estimation method. The coefficient on the log difference of capital stocks, dK, enters positively and significantly at the 1% confidence level in all the specifications. The capital coefficient estimate for the full sample regression is approximately 0.5.

The coefficient on log differences in 'labor', measured by both reported labor and population stocks, dL, also enters with the expected positive coefficient,

[5]These results are available upon request. In addition, the labor force estimate for Gabon in 1965 appeared to be particularly unreliable, implying a 94% participation rate. The reported results below exclude the country of Gabon. However, none of the qualitative results change when Gabon is included.

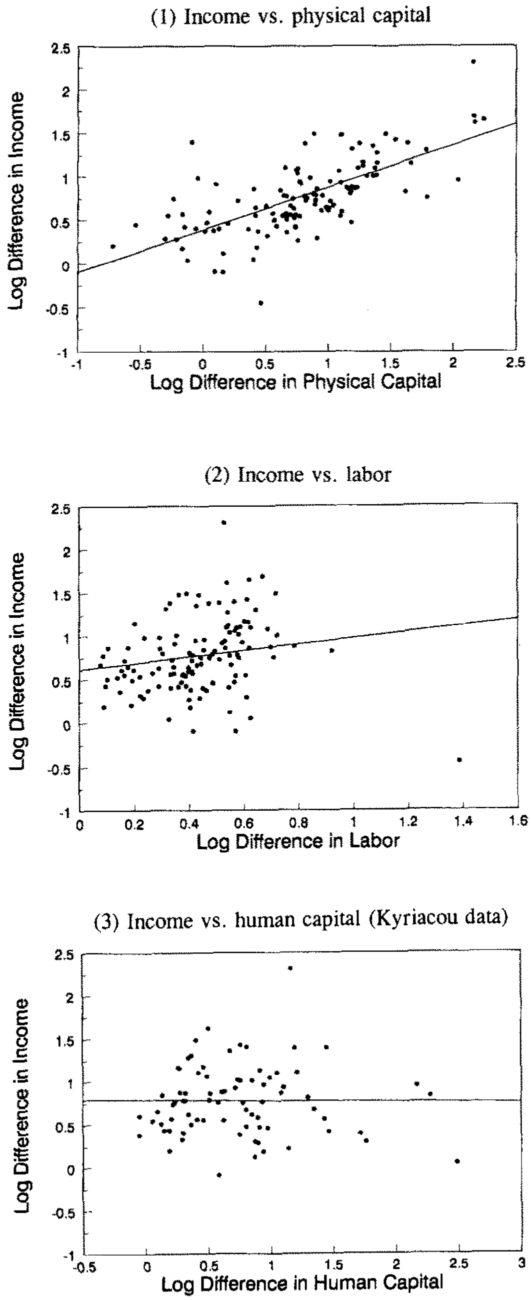

Fig. 1. Growth in income vs. factor accumulation.

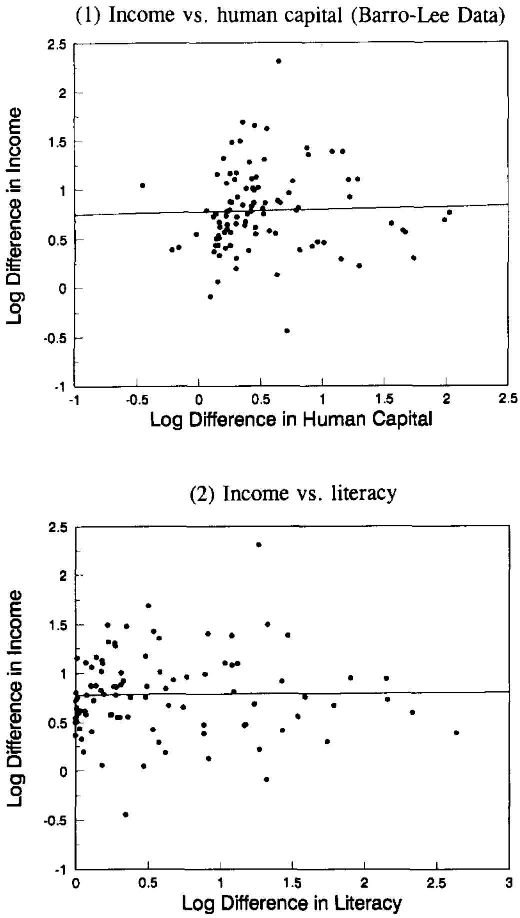

Fig. 2. Alternative measures of human capital.

although the coefficient estimate appears to be low and the variable rarely enters significantly at a 5% confidence level.[6]

The most surprising result concerns the coefficient on the log difference in human capital, dH. The log difference in human capital always enters insignificantly, and almost always with a negative coefficient. One explanation for the negative coefficient is that a number of countries, most notably many from

[6]When we exclude Botswana, the coefficient on physical labor growth increases to 0.27, while the other results are similar.

Table 1
Cross-country growth accounting results: Standard specification[a] – dependent variable: DY 1965–1985

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Const.	0.269[b] (0.090)	1.947[b] (0.322)	1.871[b] (0.349)	1.968[b] (0.398)	1.127[b] (0.287)	1.654[b] (0.296)
DK	0.457[b] (0.085)	0.545[b] (0.066)	0.555[b] (0.068)	0.530[b] (0.088)	0.607[b] (0.064)	0.472[b] (0.056)
DL	0.209 (0.207)	0.130 (0.163)	0.164 (0.164)	0.225 (0.192)	0.362[c] (0.156)	0.219 (0.138)
DH	0.063 (0.079)	− 0.059 (0.058)	− 0.043 (0.066)	− 0.080 (0.064)	− 0.028 (0.065)	− 0.031 (0.059)
$LOGY_0$	—	− 0.190[b] (0.036)	− 0.185[b] (0.038)	− 0.190[b] (0.041)	− 0.143[b] (0.038)	− 0.152[b] (0.030)
OIL		—	− 0.097 (0.141)	—	—	
$AFRICA$	—	—	—	− 0.024 (0.144)	—	—
$LAAMER$	—	—	—	− 0.107 (0.065)		—
MID	—	—	—	—	0.675 (0.761)	—
PIQ	—	—	—	—	—	− 0.057 (0.057)
Obs.	78	78	78	78	40	67
F-stat.	26.609	37.693	30.228	25.610	27.740	22.736

[a]dX refers to the log difference in variable X. Standard errors are in parentheses.

[b]1% confidence level.

[c]5% confidence level.

Africa, began the period with extremely low stocks of human capital. Consequently, those that achieved a modicum of improvement in their educational levels were credited with large improvements in this stock. However, it is well-known that many of these countries did not experience similar improvements in output, implying a small coefficient for γ in the growth accounting regressions. Nevertheless, even when we include African and Latin American country dummies, *AFRICA* and *LAAMER*, to account for the special experiences of these countries (Model 4), the results hold. Therefore, even though the experience of these countries over the period provides evidence against the standard growth accounting framework, these countries alone do not drive the results found in Table 1.[7]

Also, note that these country dummies, as well as the dummy for oil-exporting countries in Model 3, fail to enter significantly once one accounts for disparities in rates of factor accumulation. It seems that proper accounting for capital and labor obviate the necessity for including these dummies. Many previous works which did not include factor accumulation due to lack of capital stock data, such as Barro (1991), found that these dummies entered significantly.

The negative point estimate on human capital accumulation is robust to the inclusion of the log of initial wealth, $LOGY_0$, and cannot be explained by the negative correlation between human capital accumulation and initial income per worker. Initial income itself robustly enters with a negative and highly significant parameter estimate.

We should note that for a specification with an aggregate production function the accumulation of factors are accounted for, and the role of initial income in our regressions is unclear. However, initial income may proxy for initial technological advantage and, as argued in the next section, the negative coefficient may be interpreted as a 'catch-up' result.

Models 5 and 6 introduce ancillary variables to incorporate other factors which may play a role in determining per capita growth rates. *MID* represents the relative size of the middle class in a country and is the variable used as a measure of income distribution by Persson and Tabellini (1991). Note that the sample size available with the introduction of this variable is much smaller, as income distribution data is relatively scarce. Once one adjusts for differences in rates of factor accumulation, this ancillary variable fails to significantly affect growth, contrary to Persson and Tabellini (1991). However, the variable does enter with the expected positive sign.

The final model introduces political instability, *PIQ*, measured as average annual levels of the political instability coefficient, obtained from Gupta (1990).[8] Note that once again the political instability variable fails to enter significantly once one accounts for differences in rates of factor accumulation.

The factor accumulation parameter estimates exhibit stability with respect to the inclusion of various combinations of these ancillary variables. This stability is desirable in the light of studies which show that the results of cross-country growth accounting of this type are likely to be sensitive to the specification chosen (Levine and Renelt, 1992).

[7]Using maximum likelihood techniques, we also ran a C.E.S. specification. The elasticity of substitution was not measurably different from one. The implied factor shares with a unitary elasticity were about 0.5 each for physical capital and labor, while human capital was still insignificant with a point estimate of 0.03.

[8]Gupta (1990) uses discriminant analysis of a variety of political events from the Taylor and Jodice (1983) data set to form his index of political instability.

Table 2
Cross-country growth results: Alternative data and specifications[a] – dependent variable: *DY* 1965–1985

	Model 1	Model 2	Model 3	Model 4[b]	Model 5[c]	Model 6[d]
Const.	1.947[e]	1.707[e]	2.022[e]	1.380[e]	1.959[e]	1.932[e]
	(0.322)	(0.294)	(0.377)	(0.281)	(0.341)	(0.429)
DK	0.545[e]	0.585[e]	0.589[e]	0.536[e]	0.522[e]	0.554[e]
	(0.066)	(0.053)	(0.061)	(0.068)	(0.073)	(0.069)
DL	0.130	– 0.022	0.030	0.214	0.153	0.183
	(0.163)	(0.139)	(0.138)	(0.133)	(0.217)	(0.169)
DH	– 0.059	—	—	– 0.090	– 0.092	– 0.062
	(0.058)			(0.058)	(0.068)	(0.076)
DHB	—	– 0.026	—	—	—	—
		(0.071)				
DLIT	—	—	– 0.041	—	—	—
			(0.057)			
$LOGY_0$	– 0.190[e]	– 0.166[e]	– 0.201[e]	– 0.129[e]	– 0.185[e]	– 0.191[e]
	(0.036)	(0.030)	(0.041)	(0.028)	(0.038)	(0.045)
Obs.	78	97	96	53	57	71
F-stat.	37.693	52.541	37.862	33.208	25.801	38.646

[a]d*X* refers to the log difference in variable *X*. Standard errors are in parentheses.
[b]Excludes African countries.
[c]Excludes Latin American countries.
[d]Excludes oil-exporting countries.
[e]1% confidence level.

To test the robustness of our results for the effect of human capital growth on output growth, we experimented with both alternative data and alternative subsamples of the complete Summers–Heston data set. The results of these exercises are shown in Table 2. Models 1, 2, and 3 show the results for growth in human capital for the Kyriacou (1991), d*H*, Barro and Lee (1993), d*HB*, and literacy, d*LIT*, proxies for human capital respectively.[9] It can be seen that growth in human capital enters insignificantly using all three measures. Models 4, 5, and 6 show the robustness of the results to alternative subsamples of the data, excluding the African, Latin American, and oil-exporting countries,

[9]Since literacy data for 1965 across countries was very limited, we used data for 1960. The data therefore reflect growth in literacy from 1960 through 1985.

Table 3
Cross-country income determination in levels[a] – dependent variable: *LOGY*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Const.	0.744	0.584	0.569	2.399[b]	2.196[b]	2.250[b]
	(0.568)	(0.391)	(0.521)	(0.325)	(0.350)	(0.385)
LOGK	0.853[b]	0.871[b]	0.866[b]	0.643[b]	0.692[b]	0.694[b]
	(0.064)	(0.048)	(0.049)	(0.038)	(0.038)	(0.030)
LOGL	0.153[c]	0.136[b]	0.155[b]	0.365[b]	0.319[b]	0.318[b]
	(0.066)	(0.055)	(0.051)	(0.041)	(0.042)	(0.033)
LOGH	0.050	—	—	0.217[b]	—	—
	(0.071)			(0.076)		
LOGHB	—	0.015	—	—	0.039	—
		(0.047)			(0.078)	
LOGLIT	—	—	0.037	—	—	0.080
			(0.049)			(1.003)
Obs.	80	97	115	109	101	102
F-stat.	893.10	1284.68	1197.91	1218.24	1130.18	1173.73

[a]Models 1, 2, and 3 use 1965 data, with the exception of Model 3 for which LOGLIT refers to 1960 literacy rates. Models 4, 5, and 6 use 1985 data.

[b]1% confidence level.

[c]5% confidence level.

respectively. It can be seen that growth in human capital enters negatively and with the incorrect sign in all three subsamples.[10]

We may at his point compare our results to those of Mankiw, Romer, and Weil (1992). In their first set of regressions Mankiw, Romer, and Weil estimate the coefficients of the production function by regressing output levels on labor and physical and human capital. They do not use data for stocks, however, but are able to proxy for stocks using the flows of investment and school enrollment rates by assuming countries are in a steady state in the context of an augmented Solow model. Their estimates are obtained using output data for 1985 and averages for investment flows from 1960 through 1985. Using our physical capital stock data, we can run their specification in levels for individual years.

Our results for the specification in levels using different measures of human capital for the beginning and ending years of the sample are shown in Table 3.

[10]As an additional test of robustness, we also used the same specification with cross-state manufacturing data for the United States. Our results were similar in the sense that differences in human capital were insignificant. Log levels of human capital, consistent with our specification below, entered with positive sign, but were insignificant, perhaps due to lack of much variation in education levels across U.S. states. These regressions were reported in an earlier version of this paper and are available upon request.

Using the Kyriacou human capital measure, we can reproduce their result that human capital enters in levels in explaining income (Y) in 1985, but not in 1965. This is not surprising, since we found that human capital did not enter into log differences above. In addition, neither the Barro–Lee measure of human capital nor the literacy measure enters significantly in explaining income for either the beginning or ending year of the period.

The augmented Solow model with human capital implies that the growth of output will be proportional to the distance of current output from its steady state, which is of course a function of steady state physical capital stocks and labor. Again, using steady state flows to proxy for steady state stocks, Mankiw, Romer, and Weil test this formulation by regressing growth in output on current income, on flows of investment, and on secondary school enrollments. They obtain estimates for the coefficients on labor and the stocks of physical and human capital in the production function, as well as the coefficient on initial income, which turns out to be negative and implies conditional convergence. Above (Table 1), we estimate a closely related equation without making the steady state assumptions. In addition to initial income, we use the growth of physical and human capital stocks over the period 1965–1985 as independent variables to explain the growth of income. While we also obtain a negative coefficient on initial income, the coefficient for human capital is insignificant and enters with the wrong sign.[11] Moreover, as we see in Table 2, this result is independent of whether we use the Kyriacou, Barro–Lee, or literacy data sets as proxies for the stock of human capital in computing the growth rates of human capital.

Nevertheless, if we interpret the school enrollment variable in the conditional convergence regressions of Mankiw, Romer, and Weil as a proxy for an average level of human capital stocks, then their regressions would be in close accord with our regressions in Table 4 below, where we explain the growth of income by the growth in labor, the growth in physical capital, and the average level of human capital.

3. An alternative model for growth accounting

The small role indicated for human capital in the standard growth equations is somewhat troubling. Human capital accumulation is commonly cited as

[11] Using investment as a share of income as a proxy for the capital stock may be justified under a steady state assumption, as in Mankiw, Romer, and Weil (1992). Such a proxy has been extensively used in the literature (for example, Barro, 1991). Replacing our capital stock data with investment shares does not alter our results. The growth in human capital remains insignificant in explaining the growth of output.

a prerequisite for development and most countries have government policies which encourage human capital accumulation.

However, Nelson and Phelps (1966)[12] suggested that simply including an index of education or human capital as an additional input would represent a gross misspecification of the productive process. Instead, they argued that education facilitates the adoption and implementation of new technologies, which are continuously invented at an exogenous rate. In particular, they suggested that the growth of technology, or the Solow residual, depends on the gap between its level and the level of 'theoretical knowledge', $T(t)$,

$$\frac{\dot{A}}{A} = c(H)\left[\frac{T(t) - A(t)}{A(t)}\right]. \tag{2}$$

One can see through the specification in Eq. (2) that the rate at which the gap is closed will depend on the level of human capital, H, through the function, $c(H)$, where $\partial c/\partial H > 0$. The theoretical level of knowledge is taken to grow exponentially, so that $T(t) = T(0)e^{\lambda t}$. This model implies that the Solow residual, or the growth of total factor productivity, is influenced by H in the short run. However, in the long run, the Solow residual must settle down to a rate of λ.

More recent theories have modeled the growth of A directly as a function of the educational level H, emphasizing the endogenous nature of growth and technical progress (for example, Lucas, 1988). Romer (1990b) has studied the role of market incentives that determine the allocation of H between the production of goods and inventive activities which enhance the growth of A, while treating the total quantity of H as exogenous. For simplicity, we will abstract from these important issues relating to the allocation and production of H. We assume that H is exogenously given and that a higher level of H causes a higher level of growth in A.

For the purpose of our cross-country comparisons, however, we cannot ignore the diffusion of technology between countries. We adapt the Nelson and Phelps (1966) framework to allow for the 'catch-up' of technology, not to an exogenously growing theoretical level of knowledge, but to the technology of the leading country. More precisely, for a country i we specify the growth rate of total factor productivity as follows:

$$\frac{\dot{A}_i(t)}{A_i(t)} = g(H_i) + c(H_i)\left[\frac{\max_j A_j(t) - A_i(t)}{A_i(t)}\right], \qquad i = 1, \ldots, n, \tag{3}$$

[12]More recently, Romer (1990b) has also argued that the level of human capital may have an influence on growth of A, both directly and through its effect on the speed of the 'catching-up' process.

where the endogenous growth rate $g(H_i)$ and the catch-up coefficient are nondecreasing functions of H_i. Therefore, the level of education not only enhances the ability of a country to develop its own technological innovations, but also its ability to adapt and implement technologies developed elsewhere.

Eq. (3) then represents a system of differential equations which are easily analyzed. First we note that a lead country with the highest initial A, say $A_L(0)$, will be over taken by some other country that has a higher level of education. This follows because the lead country grows at the rate $g(H_L)$, or:

$$A(t) = A_L(0)\mathrm{e}^{g(H_L)t},$$

while the growth rate of a country with a higher H, say H_i, is larger than $g(H_i)$ since it is also affected by the catch-up factor. Thus

$$A_i(t) > A_i(0)\mathrm{e}^{g(H_i)t},$$

and since $g(H_i) > g(H_L)$, there exists some τ such that, for $t > \tau$, $A_i(t) > A_L(t)$. Once country i is in the lead however, it can also be overtaken by another country with a lower initial level of technology $A_j(0)$ $[A_j(0) < A_L(0)]$, but which has a higher level of education, such that $g(H_j) < g(H_L)$.

Note that the technology level A_L of a leader country L cannot be overtaken by another country with a lower level of education. If the follower country, say F, ever caught up, we would have $A_L = A_F$ and the catch-up component of the growth in A's would be equalized, leaving the country with the higher education level to surge ahead.[13]

The observations above imply that irrespective of the distribution of initial levels of technology, given by the vector $A(0)$, at some time $\hat{t}$ the country with the highest level of education must overtake the technology level of all other countries and maintain that lead into the future, unless of course it loses its educational advantage. The dynamics of technology can then easily be characterized beyond $\hat{t}$, and without loss of generality we take $\hat{t} = 0$. The technology level of the leading country, say m, grows at the rate $g(H_m)$, so that

$$A_m(t) = A_m(0)\mathrm{e}^{g(H_m)t}.$$

In general, the growth rates of A_i, for every i, are given by

$$\frac{\dot{A}_i(t)}{A_i(t)} = g(H_i) + c(H_i)\left[\frac{A_m(0)\mathrm{e}^{g(H_m)t} - A_i(t)}{A_i(t)}\right], \tag{4}$$

[13]For the leading country with the highest A, say A_m, this would be true even if the functions $c(H)$ differed across countries since $\max_j A_j - A_m = 0$.

which can be simplified to

$$\frac{\dot{A}_i(t)}{A_i(t)} = [g(H_i) - c(H_i)] + c(H_i)\left[\frac{A_m(t)}{A_i(t)}\right]. \tag{5}$$

This equation has a simple solution:

$$A_i(t) = [A_i(0) - \Omega A_m(0)\mathrm{e}^{[g(H_i) - c(H_i)]t} + \Omega A_m(0)\mathrm{e}^{g(H_m)t}], \tag{6}$$

where

$$\Omega = \left(\frac{c(H_i)}{c(H_i) - g(H_i) + g(H_m)}\right). \tag{7}$$

In the case studied by Nelson and Phelps (1966), $g(H_i) = 0$ and H_i affects the growth of A_i only in transition: The asymptotic growth rate is given by the exogenous growth rate of technology. In the case above, the effects of $g(H_i)$ on the growth of A_i persist longer if $g(H_i) > c(H_i)$ and the convergence to a common growth rate will be slower than in the model of Nelson and Phelps (1966). Nevertheless, in the long run, the leader must still set the pace as the growth induced by $g(H_m)$ eventually overwhelms the other growth component $g(H_i)$ in each country. This can immediately be seen from the asymptotic ratio $A_i(t)/A_m(t)$:

$$\lim_{t\to\infty} \frac{A_i(t)}{A_m(t)} = \lim_{t\to\infty}\left[\frac{A_i(0) - \Omega A_m(0)}{A_m(0)}\right]\mathrm{e}^{[g(H_i) - c(H_i) - g(H_m)]t} + \Omega, \tag{8}$$

which simplifies to

$$\lim_{t\to\infty} \frac{A_i(t)}{A_m(t)} = \Omega, \tag{9}$$

since $[g(H_i) - c(H_i) - g(H_m)] < 0$. It follows that A_i and A_m asymptotically grow at the same rate $g(H_m)$. In the long run, the country with the highest level of H acts as the 'locomotive' of growth by expanding the set of attainable knowledge, pulling all others along through the catch-up effect, and all countries grow at the same rate.

Nonetheless, a few simple simulations show that the transition period may be extremely long. Note also that a country with a very low level of A can have a much higher growth rate than the leader because of the catch-up effect, while others that are closer to the leader, both in their technology level and their educational attainment, may in fact have lower growth rates than the leader because the catch-up effect may be insignificant relative to the educational gap. It follows that it may be difficult to observe the positive effect of education on the growth of total factor productivity. Therefore, to the extent that low educational attainment leads to or is associated with low levels of technology and income, it may be necessary to control for the catch-up effect by including the income (or technology) levels in our regressions. The empirical results below tend to confirm these observations.

Finally, the analysis above has ignored the possible positive feedback effects from technology or income growth to the level of education. If educational levels tend to increase with incomes, growth rates may also diverge.[14]

4. Growth accounting with human capital stocks entering into productivity

The alternative model presented above provides two mechanisms by which levels of human capital stocks can influence per capita income growth along the transition path. First, the endogenous growth component, $g(H_i)$, has an influence on relative growth rates of technology directly. Second, the catch-up component, which is specified as dependent upon the stock of human capital possessed by a country in the spirit of Nelson and Phelps, also allows levels of human capital to enter into per capita income growth.

It follows that the current model allows for human capital effects to enter in levels, at least in transition before the growth rates of A_i catch up to that of the leader nation. To incorporate this possibility, we adopt a new specification to replace (1):[15]

$$\begin{aligned}(\log Y_T - \log Y_0) &= (\log A_T - \log A_0) + \alpha(\log K_T - \log K_0) \\ &\quad + \beta(\log L_T - \log L_0) + \gamma\left(1/T\sum_0^T \log H_t\right) \\ &\quad + (\log \varepsilon_T - \log \varepsilon_0). \qquad (1')\end{aligned}$$

Eq. (1′) differs from (1) in that the term with the log difference in human capital has been replaced with the average level of the log of human capital over the period. However, because we do not have yearly data on H_t, we use $1/2\,(\log H_T + \log H_0)$ in the subsequent regressions as a proxy for the log of the average level of human capital. We also ran the average levels of human capital and the log of the average levels. These yielded similar results to those reported below.

Table 4 reports the results of ordinary least squares estimation using White's heteroskedasticity correction method. Model 1 simply substitutes the log of

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[14] Unless, of course, diminishing returns to education sets in. That is, if the functions g and c in (4) asymptotically become flat.

[15] This specification is consistent with a competitive model of technology diffusion in which the rate of human capital accumulation is endogenously determined. See Benhabib and Rustichini (1993).

Table 4
Cross-country growth accounting results: Human capital in log levels[a] – dependent variable: *DGDP* 1965–1985

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Const.	0.416[b] (0.103)	2.093[b] (0.326)	2.065[b] (0.345)	2.044[b] (0.392)	1.176[b] (0.391)	1.730[b] (0.308)
DK	0.495[b] (0.100)	0.500[b] (0.075)	0.505[b] (0.079)	0.479[b] (0.094)	0.594[b] (0.077)	0.440[b] (0.063)
DL	0.132 (0.218)	0.253 (0.166)	0.260 (0.169)	0.391[c] (0.191)	0.385[c] (0.174)	0.303 (0.150)
LOGH	– 0.079 (0.060)	0.128[c] (0.055)	0.121[c] (0.059)	0.167[c] (0.054)	0.045 (0.101)	0.089 (0.058)
$LOGY_0$	—	– 0.233[b] (0.043)	– 0.230[b] (0.045)	– 0.235[b] (0.046)	– 0.161 (0.067)	– 0.179[b] (0.036)
OIL	—	—	– 0.032 (0.127)	—	—	—
AFRICA	—	—	—	0.007 (0.133)	—	—
LAAMER	—	—	—	– 0.135[c] (0.065)	—	—
MID	—	—		—	0.746 (0.747)	—
PIQ	—	—	—	—	—	– 0.045 (0.053)
Obs.	78	78	78	78	40	67
F-stat.	27.551	41.225	32.583	29.198	27.832	23.830

[a]d*X* refers to the log difference in variable *X*. Standard errors are in parentheses.

[b]1% confidence level.

[c]5% confidence level.

average human capital levels for log differences of human capital. Physical capital accumulation and labor force growth enter with their predicted signs, but labor force growth fails to enter significantly. However, the performance of human capital appears disappointing. Both in levels and in growth rates, human capital fails to enter significantly, and the point estimates are of incorrect sign.

Nevertheless, as pointed out above, the human capital rich country need not always be the high growth country because of the catch-up factor. Therefore, Model 1 is likely to be misspecified. To account for differences in initial technology levels across countries, we introduce initial income levels in Model 2, which will capture the role of the catch-up effect.[16]

As soon as initial income levels are introduced, human capital enters significantly in levels with the predicted positive sign. This result suggests that catch-up remains a significant element in growth, and that countries with higher education tend to close the technology gap faster than others. It is not particularly surprising that this transition effect appears in twenty years of growth experiences. The transition towards a common growth rate set by the leading country may be quite long, and stochastic technological innovations by the leader can set countries on new transition paths. The results suggest that the role of human capital is indeed one of facilitating adoption of technology from abroad and creation of appropriate domestic technologies rather than entering on its own as a factor of production.[17]

In addition, we used likelihood ratio tests to examine whether human capital in levels should be added to a regression which included growth rate of population and physical and human capital as well as initial per capita income. The likelihood tests indicated that human capital in levels should be included in the specification with a 1% level of confidence.

Initial income enters significantly and negatively in all the specifications. This may imply some support for the convergence hypothesis. However, given the model above, a negative coefficient estimate on initial income levels may not be a sign of convergence due to diminishing returns, but of catch-up from adoption of technology from abroad. These two forces may be observationally equivalent in simple cross-country growth accounting exercises.

The ancillary variables are introduced in Models 3 through 6. The positive and significant coefficient estimate on levels of human capital is robust to the introduction of these variables, with the exception of the income distribution variable *MID*. However, the sample size is severely curtailed by the introduction of this variable.

With the exception of the Latin American dummy, note that none of the ancillary variables are statistically significant at the 5% confidence level. As above, once one accounts for differences in rates of factor accumulation, the

[16]Strictly speaking, the previous section suggests that the catch-up term should be $\log(Y_{\max} - Y_i)$, where $Y_{\max}$ is the initial income per worker for the leading country. Since $Y_{\max}$ is constant across countries, it enters into the constant term which can no longer be viewed, unlike Model 1, as accounting for exogenous growth. If the catch-up is operative at higher frequencies, such as annually, then the modified specification requires us to include not initial income, but an average of incomes over the years as well as adjusting the constant term for changes in $Y_{\max}$.

[17]One caveat is again the possibility of a bias in these coefficient estimates as discussed in Section 2 and in the Appendix. However, the coefficient estimates on physical capital are close to its expected factor share and do not indicate a significant upward bias.

residual role for characteristics such as political stability and skewness of income distribution appears to be limited.

5. A more structural specification

While the specification in Eq. (1′) was consistent with the spirit of the alternative theoretical model above, a more structural model is required to generate a specification which follows directly from the theory. In this section we develop and test such a specification.

Assuming a Cobb–Douglas technology, $Y_t = A_t(H_t)K_t^{\alpha}L_t^{\beta}$, and taking log differences, the relationship for long-term growth from time 0 to time T can be specified as

$$(\log Y_T - \log Y_0) = [\log A_T(H_t) - \log A_0(H_t)] + \alpha(\log K_T - \log K_0) + \beta(\log L_T - \log L_0) + (\log \varepsilon_T - \log \varepsilon_0). \tag{10}$$

Following the discussion above, we specify the first term in Eq. (10), the growth of total factor productivity, to depend on two factors. The first is the level of human capital, reflecting the effect of domestic endogenous innovation. The second is an interactive term that involves the level of human capital and the technological lag of a country behind the leader, to capture the 'catch-up' effects. Consider the following structural specification for a representative country i:

$$[\log A_T(H_t) - \log A_0(H_t)]_i = c + gH_i + mH_i[(Y_{\max} - Y_i)/Y_i], \tag{11}$$

where c represents exogenous technological progress, gH_i represents endogenous technological progress associated with the ability of a country to innovate domestically, and $mH_i[(Y_{\max} - Y_i)/Y_i]$ represents the diffusion of technology from abroad. While the 'domestic innovation' term indicates that human capital stocks independently enhance technological progress, the 'catch-up' term suggests that holding human capital levels constant, countries with lower initial productivity levels will experience faster rates of growth of total factor productivity. Simplifying, Eq. (11) can then be written

$$[\log A_T(H_t) - \log A_0(H_t)]_i = c + (g - m)H_i + mH_i(Y_{\max}/Y_i). \tag{12}$$

Inserting (12) into (10) then yields

$$(\log Y_T - \log Y_0) = c + (g - m)H_i + mH_i(Y_{\max}/Y_i) + \alpha(\log K_T - \log K_0) + \beta(\log L_T - \log L_0) + (\log \varepsilon_T - \log \varepsilon_0). \tag{13}$$

Estimation of Eq. (13) using ordinary least squares with White's heteroskedasticity correction is reported in Table 5. Model 1 shows the results for

Table 5
'Structural specification' cross-country growth regressions[a] – dependent variable: DY 1965–1985

	Model 1	Model 2[b]	Model 3[c]	Model 4[d]	Model 5
Const.	0.1627	– 0.2268	0.0528	0.2324	0.0538
	(0.1142)	(0.2822)	(0.2246)	(0.2483)	(0.1345)
H	– 0.0136	0.0439[g]	– 0.0003	– 0.0736	0.0021
	(0.0144)	(0.0224)	(0.0366)	(0.0586)	(0.0154)
$H(Y_{max}/Y)$	0.0011[e]	0.0003	– 0.0001	0.0012[e]	0.0007[f]
	(0.0002)	(0.0009)	(0.0009)	(0.0003)	(0.0003)
dK	0.4723[e]	0.5076[e]	0.5517[e]	0.5233[e]	0.5005[e]
	(0.0717)	(0.0944)	(0.1226)	(0.1431)	(0.0771)
dL	0.1880	0.1720	0.5389	0.2901	0.2045
	(0.1640)	(0.2325)	(0.3884)	(0.5069)	(0.1558)
Y_{max}/Y	—	—	—		0.0014
					(0.0010)
Obs.	78	26	26	26	78
F-stat.	45.245	9.778	11.136	18.471	37.667

[a]Ordinary least squares. White's heteroskedasticity correction used. Standard errors are in parentheses.

[b]Wealthiest third of sample; per capita GDP in 1965 greater than $2520.

[c]Middle third of sample; per capita GDP in 1965 less than $2520 and greater than $1250.

[d]Poorest third of sample; per capita GDP less than $1250.

[e]1% confidence level.

[f]5% confidence level.

[g]10% confidence level.

the full 78-country sample for which data is available. The 'catch-up' term $[H(Y_{max}/Y)]$ enters positively and significantly for the large sample. However, the coefficient estimate for $(g - m)$ on H is negative and insignificant. Moreover, the point estimate of $(g - m)$ is sufficiently large in absolute value that the point estimate for g, that is the coefficient on country-specific technological progress, is negative.[18]

The results of Model 1 appear to favor catch-up over endogenous country-specific technological progress as the channel through which accumulation of human capital affects productivity growth. However, this may change with the relative position of the country. In particular, technology adoption from

[18]Using bootstrap procedures, we estimated the standard errors of the estimates of g for the reported models. All of the estimates fail to be significant at a 5% confidence level, although that of Model 4 was significant at a 10% level as reported below.

abroad may be more effective for countries at low levels of development rather than development of domestic technology, while the opposite may be true for technologically-advanced countries. To examine this conjecture, we separate the model into three equivalent samples on the basis of initial per capita income.[19]

The results of Model 2, with the sample containing the poorest third of countries, are similar to those found for the full sample. While the catch-up term is positive and significant, the point estimate for the domestic innovation term is negative.

Model 3 shows the results of the specification for the middle group. For this sample, the catch-up and the domestic innovation terms are very insignificant, indicating that the level of human capital fails to play an important role through either channel.

We obtain the most striking results from the richest third of the sample, as reported in Model 4. For the richest third of the nations, the catch-up term becomes relatively unimportant, entering insignificantly and with a coefficient estimate which is positive, but very close to zero.

However, the term $(g - m)$ now enters positively and significantly with a 6% level of confidence. Considering the relatively small size of the sample, this represents a dramatic break with the other nations in the study. Using bootstrap procedures to obtain the standard error of g, we find that g is positive at a 10% confidence level.

Finally, we introduce initial income in Model 5 to demonstrate that the results for our interactive parameter are not simply being driven by a neo-classical convergence effect. It can be seen that our 'catch-up' term is robust to the inclusion of this variable, maintaining its proper sign and significance.

6. Determinants of physical capital accumulation

Finally, we examine an alternative channel for human capital to contribute to growth: Human capital may encourage accumulation of other factors necessary for growth, particularly physical capital. Lucas (1990) has suggested that one reason that physical capital does not flow to poor countries may be that these countries are poorly endowed with factors complementary to physical capital, so that the marginal product of physical capital in developing countries may not actually be that high, despite its apparent scarcity relative to the developed countries.[20]

[19]Dividing the sample in two yielded similar results.

[20]However, income-to-capital ratios in the current data set are negatively related to income levels at a 5% confidence level. Therefore, assuming a Cobb–Douglas or C.E.S. specification, poorer countries should have higher returns to physical capital inputs.

Table 6
Determinants of physical capital accumulation 1965[a] – dependent variable: DK/K

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Const.	– 0.004	– 0.003	0.019	0.031	– 0.003	– 0.013	0.047
	(0.007)	(0.007)	(0.015)	(0.033)	(0.013)	(0.025)	(0.005)
K	– 1.87E-11[b]	– 1.86E-11[b]	– 1.26E-11[c]	– 9.60E-12	– 1.74E-11[b]	2.48E-12	1.92E-12
	(5.61E-12)	(5.70E-12)	(6.41E-12)	(6.56E-12)	(5.34E-12)	(6.71E-12)	(7.83E-12)
H	0.010[b]	0.010[b]	0.007[b]	0.006[c]	0.010[b]	—	—
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)		
L	2.36E-07[c]	2.37E-07[c]	1.28E-07	8.61E-08	1.76E-07	1.03E-08	4.02E-07[b]
	(1.03E-07)	(1.06E-07)	(1.08E-07)	(8.34E-08)	(1.22E-07)	(7.81E-08)	(1.28E-07)
OIL	—	0.005	—	—	—	—	—
		(0.015)					
AFRICA	—	—	– 0.028[c]	—	—	—	—
			(0.014)				
LAAMER	—	—	– 0.005	—	—	—	—
			(0.010)				
MID	—	—	—	– 0.031	—	0.166[c]	—
				(0.112)		(0.072)	
PIQ	—	—	—	—	0.002	—	– 0.026[b]
					(0.008)		(0.007)
Obs.	80	80	80	40	70	50	97
F-stat.	12.556	9.341	9.239	1.789	8.163	1.517	6.889

[a] dK/K is measured as 1966 capital stock minus 1965 capital stock divided by capital stock in 1965. Standard errors are in parentheses.

[b] 1% confidence level.

[c] 5% confidence level.

Similarly, a variety of studies (for example, Alesina et al., 1992; Persson and Tabellini, 1991) have shown that political instability or a skewed income distribution is negatively correlated with economic growth. This raises the possibility that, while political instability or a skewed income distribution does not directly affect growth, it may have a negative effect on factor accumulation. Kormendi and Meguire (1985) have argued that political instability will be negatively correlated with physical capital accumulation because of lack of faith in the assignment of property rights. They demonstrate a negative correlation between proxies for political instability and gross investment as a share of income.

If we assume that adjustment of physical capital stocks is costly in the short run, one would expect to find some cross-country differences in marginal products of capital which were not immediately removed through capital flows. However, one would also expect that rates of capital accumulation, or $\mathrm{d}K/K$, would tend towards equating these differences in marginal product, holding all else equal. Under a standard adjustment process, it follows that $\mathrm{d}K/K$ should be positively correlated with the current marginal product of capital, which in turn depends on the current stocks of labor and physical and human capital. Similarly, it follows that ancillary determinants of the expected return on investment, such as political instability, may also enter into investment as a share of the capital stock.

We examine the determinants of physical capital accumulation in 1965 in Table 6. We regress the ratio of gross investment to capital stock on factor stocks: Human capital, physical capital, and the labor force, as well as ancillary variables including dummies for oil-exporting, African, and Latin American countries, as well as the size of the middle class, which was shown to have an impact on growth in Persson and Tabellini (1991). In addition, we introduce Gupta's measure of political instability. Physical capital consistently enters with the predicted negative sign at a 5% level of significance, with the exception of Model 4 which has the curtailed income distribution sample. Similarly, the labor force enters positively, although not always significantly, as would be predicted.

Most importantly, human capital stocks are positively correlated with physical capital accumulation and are significant at a 5% level for all specifications. This implies that the role for human capital as an agent in attracting physical capital is vindicated.

The ancillary variables, once we have accounted for factor endowments, perform very poorly. Note that both political instability and income distribution enter insignificantly and with the incorrect sign. The oil-exporting dummy is highly insignificant for this period, and the regional dummies are insignificant as well, although they enter with their expected negative signs.[21]

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[21] Similar cross-country results were obtained for 1970 and 1975 and are reported in Benhabib and Spiegel (1992). In addition, we also found similar results for 1985. Notably, the 1985 regressions

The data lends support to the conjecture that human capital may be an important feature in attracting physical capital. Since we know from the growth equations that physical capital accumulation rates play a very important role in determining the rates of per capita income growth, the importance of this role is apparent.

The performance of the ancillary variables is somewhat surprising. As was the case above, we found that once one accounted for stocks of factor endowments, there was little role left to play for both income distribution and political instability. However, we should be careful to note that human capital levels are highly correlated with these ancillary variables. This implies the possibility that multicollinearity may be precluding these ancillary variables from entering into the determination of cross country investment shares. When human capital is omitted from the regression, income distribution and political instability enter with their respective predicted signs and are usually statistically significant, however exchange rate overvaluation is still statistically insignificant.

7. Conclusion

Human capital accumulation has long been considered an important factor in economic development. The results obtained in our initial set of regressions are therefore somewhat disappointing: When one runs the specification implied by a standard Cobb–Douglas production function which includes human capital as a factor, human capital accumulation fails to enter significantly in the determination of economic growth, and even enters with a negative point estimate.

When we introduce a model in which human capital influences the growth of total factor productivity we obtain more positive results. In this model, human capital affects growth through two mechanisms. First, human capital levels directly influence the rate of domestically produced technological innovation, as in Romer (1990a). Second, the human capital stock affects the speed of adoption of technology from abroad, in the spirit of Nelson and Phelps (1966). The significance of this alternative model in terms of its empirical implications is that human capital stocks in levels, rather than their growth rates, now play a role in the determining the growth of per capita income.

Treating human capital as a factor of production implies that in the growth accounting regressions human capital should enter in growth rates. However, our empirical findings fail to deliver this result. We introduce two alternative

included a proxy for openness obtained from Dollar (1992). As was the case for the political instability variable, the openness variable entered into the determination of physical investment only in the absence of accounting for human capital accumulation. These results are available upon request.

avenues through which human capital can play a role in economic growth: Both as an engine for attracting physical capital and as a determinant of the magnitude of a country's Solow residual. These theories are vindicated to some degree by the empirical evidence from aggregate cross-country data.

Appendix

A.1. Estimation of aggregate physical capital stocks

Investment flow data is now available for a large number of countries from the Summers–Heston (1991) data set. However, calculation of capital stocks using this data set requires some mechanism by which initial capital stocks can be estimated. The capital stock estimates used in the regressions reported above were obtained from utilizing the limited 29-country sample of the Summers–Heston (1991) data set for which capital stock data was available. In a standard three-factor neoclassical aggregate production function with constant returns, $Y = K^{\alpha} L^{\beta} H^{\gamma}$, the relationship between these variable in logs satisfies

$$\log Y = A + \alpha \log K + \beta \log L + \gamma \log H + \varepsilon. \tag{A.1}$$

For the limited sample of countries for which capital stock data was available for 1980 and 1985, our coefficient estimates for this relationship using the Kyriacou measure for H were

$$\underset{(0.235)}{\log Y = 3.391} + \underset{(0.056)}{0.614} \log K + \underset{(0.052)}{0.349} \log L + \underset{(0.198)}{0.189} \log H + \varepsilon, \tag{A.2}$$

where standard errors are given in parentheses. The R-squared for the regression is 0.974, which is relatively large considering that we do not adjust for differences in natural resource endowments. The regression had 58 observations. We then used these coefficients to estimate initial capital stocks, K_0, for the remaining countries in the Summers–Heston data set. Capital stock estimates for subsequent years are then directly attainable according to the equation

$$K_t = K_0(1-\delta)^t + \sum_{i=1}^{t-1} I_i(1-\delta)^{t-i}, \tag{A.3}$$

where δ represents the rate of depreciation. The regressions reported above were run under the assumption of 7% depreciation, although we also generated capital stocks assuming 4% and 10% depreciation and got very similar results.

We also use alternative methodologies to estimate the initial capital stock. First, we use an iterative procedure, based upon the assumption that the relationship above would be constant across both countries and time. We started with an initial estimate of $\log K_0 - \log Y_0$ which satisfies $K_0/Y_0 = 3$ for the United States. This starting value is consistent with many estimates for this country. Then, using discounted investment flows, we find the implied series of capital stocks and calculate $\hat{\alpha}$, $\hat{\beta}$, and $\hat{\gamma}$ in Eq. (A.1). These estimated coefficients are used to update our K_0 estimates and recalculate the capital stock series. The process is repeated until convergence is achieved, i.e., until the likelihood function associated with a given set of coefficient estimates is maximized. Finally, we also simply use the output–capital ratio of three, found for the United States, to estimate the initial capital stock.

The log differences in capital stocks estimated by these processes were all very highly correlated. For example, the correlation between log differences in the capital stock used in the reported regression and that estimated by the iterative method was 98.7%. Consequently, our results do not depend upon our choice of capital stock estimation method.

A.2. Estimation of human capital stocks

Human capital stock data was obtained from Kyriacou (1991). Kyriacou estimates human capital levels from the Psacharopoulos and Arriagada (PA) (1986) data set. PA have measures of years of schooling in the labor force for 99 countries. However, these measures are from a wide variety of years, from the 1960's through the 1980's. From this large set, Kyriacou identifies 42 countries for which average years of schooling in the labor force is available for the mid-1970's: 1974–1977. He estimates the following relationship between average years of schooling in the labor force and past enrollment ratios:

$$\begin{aligned} H75 = {} & 0.0520 + 4.4390\,PRIM60 + 2.6645\,SEC70 \\ & + 8.0918\,HIGH70, \end{aligned} \tag{A.4}$$

where $H75$ represents average years of schooling in the labor force, $PRIM60$ represents the 1960 primary schooling enrollment ratio, $SEC70$ represents the 1970 secondary schooling enrollment ratio, and $HIGH70$ represents the 1970 higher education enrollment ratio. His regression has an R-squared of 82% and primary and higher education enrollment ratios enter significantly at a 5% confidence level. Kyriacou then uses these estimated coefficients to extrapolate human capital indexes for other time periods based upon past enrollment ratios.

The physical and human capital stock estimates used in this study are shown in Table 7.

A.3. Estimation of the bias

A well-known difficulty with estimating aggregative production functions is the possibility of a correlation between the error term and the regressors which would yield biased coefficient estimates. For example, a stochastic shock to the production function would typically be expected to result in the faster growth of accumulated inputs in that period. If shocks are also persistent, this will induce a positive correlation between future shocks and future levels of physical and human capital. Looking at average growth rates over long periods does not eliminate these positive correlations (Benhabib and Jovanovic, 1990). Here, we attempt to identify the sign of the biases on the estimated coefficients. If we can show that the biases on the estimated coefficients are likely to be positive, our estimates will represent upper bounds.

For example, given the specification in (1) and that H and K are correlated with the error term, while L follows an independent process, the expected bias on OLS estimates of the constant term, α, β, and γ, equal

$$\begin{bmatrix} \hat{b}_c \\ \hat{b}_K \\ \hat{b}_H \\ \hat{b}_L \end{bmatrix} = \begin{bmatrix} n & \bar{K} & \bar{H} & \bar{L} \\ \bar{K} & a_{kk} & a_{kh} & a_{kl} \\ \bar{H} & a_{hk} & a_{hh} & a_{hl} \\ \bar{L} & a_{lk} & a_{lh} & a_{ll} \end{bmatrix}^{-1} \begin{bmatrix} \bar{a} \\ a_{k\varepsilon} \\ a_{h\varepsilon} \\ 0 \end{bmatrix}, \tag{A.5}$$

where $\hat{b}_j$ is the expected bias on the estimate of coefficient j, n is the number of observations in the sample, the a_{ij} are the raw moments defined above, and bars represent mean growth rates, for example: $\bar{K} = \sum_{i,t} T_{it}^{-1}(K_{i,t+T_{it}} - K_{i,t})$. As the sample size n gets large, it is easy to show by partitioning the inverse matrix that the biases will tend towards

$$\begin{bmatrix} \hat{b}_k \\ \hat{b}_h \\ \hat{b}_l \end{bmatrix} = \begin{bmatrix} a_{kk} & a_{kh} & a_{kl} \\ a_{hk} & a_{hh} & a_{hl} \\ a_{lk} & a_{lh} & a_{ll} \end{bmatrix}^{-1} \begin{bmatrix} a_{k\varepsilon} \\ a_{h\varepsilon} \\ 0 \end{bmatrix}. \tag{A.6}$$

The determinant of the matrix, D, will be positive since the matrix is positive semi-definite. Inverting the matrix, the bias on the physical and human capital coefficients are expected to equal

$$\hat{b}_k = D^{-1}[(a_{hh}a_{ll} - a_{hl}^2)(a_{k\varepsilon}) + (a_{kl}a_{hl} - a_{kh}a_{ll})(a_{h\varepsilon})], \tag{A.7a}$$

$$\hat{b}_h = D^{-1}[(a_{kk}a_{ll} - a_{kl}^2)(a_{h\varepsilon}) + (a_{kl}a_{hl} - a_{kh}a_{ll})(a_{k\varepsilon})], \tag{A.7b}$$

$$\hat{b}_L = D^{-1}[(a_{KH}a_{KL} - a_{HH}^2)(a_{K\varepsilon}) + (a_{KH}a_{KL} - a_{KK}a_{HL})(a_{H\varepsilon})], \tag{A.7c}$$

Table 7
Capital stock data used in this study[a]

CNTRY	*K65*	*K85*	*H65*	*H85*	*CNTRY*	*K65*	*K85*	*H65*	*H85*
ALGERIA	35,120	180,215	1.409	4.657	*BRAZIL*	272,151	980,791	3.491	5.536
ANGOLA	11,913	13,073	NA	3.690	*CHILE*	45,363	65,426	5.156	6.963
BENIN	3394	3510	NA	2.335	*COLOMBI*	69,477	152,093	3.176	6.521
BOTSWAN	504	4363	1.100	3.533	*ECUADOR*	17,270	62,199	3.509	8.762
BURKINA	5519	7301	NA	0.733	*GUYANA*	3071	4597	NA	6.211
BURUNDI	2860	2752	NA	1.734	*PARAGUA*	2566	10,356	4.756	6.166
CAMEROO	7892	17,873	1.272	5.429	*PERU*	45,061	97,838	4.246	7.944
CAPE VE	447	1242	NA	NA	*SURINAM*	1615	2828	NA	6.085
CENT AF	2739	2028	0.611	3.561	*URUGUAY*	21,275	32,888	6.338	7.659
CHAD	5637	4974	0.151	1.825	*VENEZUE*	56,458	185,689	3.666	6.898
CONGO	2174	5278	2.059	NA	*AFGHANI*	13,969	12,085	NA	NA
EGYPT	16,157	48,557	NA	5.696	*BANGLAD*	56,495	47,998	NA	3.482
ETHIOPI	7139	7500	NA	1.140	*BURMA*	14,290	27,286	NA	4.939
GABON	2034	14,693	1.872	8.013	*CHINA*	1,014,664	3,551,064	NA	NA
GAMBIA	306	340	NA	1.552	*HONGKON*	20,497	88,232	NA	7.801
GHANA	11,705	9490	1.572	3.859	*INDIA*	476,072	926,307	1.931	4.751
GUINEA	4224	4812	NA	NA	*INDONES*	148,642	578,202	2.273	4.470
GUINEAB	NA	NA	0.327	2.299	*IRAN*	85,442	295,697	1.713	5.749
IVORY C	7937	17,253	0.469	4.113	*IRAQ*	40,726	244,547	1.789	4.552
KENYA	11,565	24,453	NA	3.445	*ISRAEL*	28,286	84,087	6.151	10.034
LESOTHO	733	2221	3.258	4.884	*JAPAN*	681,963	3,608,437	7.227	9.469
LIBERIA	4573	5591	1.295	3.228	*JORDAN*	2382	18,375	2.901	7.470
MADAGAS	10,370	8815	1.681	4.307	*KOREA*	39,923	350,248	4.792	7.936
MALAWI	2570	4772	1.721	1.967	*KUWAIT*	41,352	65,983	NA	6.919
MALI	4188	3171	0.345	1.444	*MALAYSI*	34,845	207,538	3.962	5.729
MAURITA	1659	3560	NA	1.029	*NEPAL*	10,924	16,653	NA	2.025
MAURITI	2281	4441	4.654	6.303	*PAKISTA*	93,956	140,879	1.847	2.540
MOROCCO	13,025	39,320	1.155	3.485	*PHILIPP*	64,730	211,298	NA	8.868
MOZAMBI	21,344	25,068	1.171	2.102	*SAUDI A*	44,282	223,459	0.303	2.951

NIGER	4497	4910	0.149	0.831	*SINGAPO*	8596	75,127	NA	6.889
NIGERIA	57,619	189,261	0.895	2.006	*SRI LAN*	24,200	67,085	NA	6.032
RWANDA	2849	2604	1.437	3.237	*SYRIA*	18,105	84,321	3.088	6.623
SENEGAL	7183	6795	0.572	2.480	*TAIWAN*	17,600	165,831	NA	4.669
SIERRA	3426	1672	0.633	1.983	*THAILAN*	39,994	160,879	3.901	5.513
SOMALIA	3963	6581	0.214	0.825	*AUSTRIA*	77,763	221,013	NA	8.574
SOUTH A	141,812	389,652	NA	NA	*BELGIUM*	123,945	257,377	NA	9.351
SUDAN	10,446	6105	0.784	2.089	*CYPRUS*	5245	12,392	NA	NA
SWAZILA	1082	3511	1.474	5.402	*DENMARK*	81,935	160,007	6.533	6.907
TANZANI	8529	18,216	0.682	1.843	*FINLAND*	76,955	175,072	NA	10.828
TOGO	1674	4103	NA	NA	*FRANCE*	629,403	1,689,367	8.672	9.539
TUNISIA	13599	29123	1.976	5.655	*GERMANY*	997,554	1,954,396	9.105	10.332
UGANDA	2728	2153	1.346	2.933	*GREECE*	40,985	138,324	6.383	8.400
ZAIRE	7145	14,991	NA	4.331	*ICELAND*	2796	6885	NA	8.558
ZAMBIA	14,724	17,313	1.602	3.830	*IRELAND*	23,697	64,542	6.256	8.830
ZIMBABW	8774	16,974	NA	4.854	*ITALY*	699,848	1,575,287	6.642	9.132
BARBADO	1676	3515	NA	8.009	*LUXEMBO*	8081	12,331	4.568	6.902
CANADA	352,837	868,868	8.018	9.984	*MALTA*	1406	4634	NA	6.823
COSTA R	4050	12,778	4.466	8.226	*NETHERL*	178,239	368,831	NA	9.475
DOMINIC	5576	22,423	3.185	6.652	*NORWAY*	70,238	169,468	NA	9.237
EL SALV	3915	7416	2.654	4.221	*PORTUGA*	34,385	109,656	3.884	6.516
GUATEMA	8014	16,467	2.054	3.676	*SPAIN*	258,431	667,000	4.136	9.699
HAITI	6094	6215	1.257	2.662	*SWEDEN*	130,904	231,996	6.690	9.635
HONDURA	2877	7150	1.904	5.643	*SWITZER*	157,791	309,388	5.722	NA
JAMAICA	8580	13,365	6.217	5.899	*TURKEY*	85,716	335,542	2.698	6.327
MEXICO	222,705	828,662	3.309	7.062	*UK*	654,292	1,180,783	7.004	8.498
NICARAG	5875	14,689	2.511	6.023	*YUGOSLA*	111,211	381,479	NA	NA
PANAMA	4216	16,707	5.239	7.989	*AUSTRAL*	232,971	534,246	6.912	8.722
TRINIDA	7856	23,897	6.206	5.916	*FIJI*	2284	5929	3.983	6.637
USA	3,596,389	7,223,147	9.821	12.086	*NEW ZEA*	37,920	79,636	7.972	9.275
ARGENTI	106,339	178,450	6.002	8.024	*PAPUA N*	5505	16,549	NA	2.799
BOLIVIA	8997	18,120	2.395	5.365					

[a] K represents physical capital in millions of dollars estimated as discussed above under 7% depreciation assumption; H represents mean years of schooling as estimated by Kyriacou (1991).

where $\hat{b}_j$ ($j = K, H, L$) represents the estimated bias, D represents the determinant of the covariance matrix, which can be signed as positive because the matrix is positive definite, and the a_{ji}'s represent the raw moments.[22]

Given that $a_{j\varepsilon} > 0$ ($j = K, H$), we can sign the first terms of both expressions as positive since the covariance matrix is positive semi-definite. However, both expressions contain the second term which has sign equal to that of the expression

$$a_{KL}a_{HL} - a_{KH}a_{LL}. \tag{A.8}$$

Since a_{KH} may well be nonegative, and a_{JL} ($J = H, K$) may also be positive because H and K are accumulated factors while L is assumed to follow an independent stochastic process, the sign of (A.8) is indeterminate, and the sign of the expected bias cannot be obtained analytically. We therefore turn to econometric evidence.

Using our sample data for 1965 through 1985 growth, we estimated the coefficients in Eq. (A.7). The standard errors of these estimates were then obtained by using a bootstrap (Efron, 1982) procedure, by creating 1000 samples from the original sample and computing the covariances of the coefficients in these created samples as population estimates of the population covariances. Our estimates of Eq. (A.7) were

$$\hat{b}_k = D^{-1}[\underset{(0.002)}{0.008}(a_{k\varepsilon}) + \underset{(0.001)}{0.002}(a_{h\varepsilon})], \tag{A.9a}$$

$$\hat{b}_h = D^{-1}[\underset{(0.003)}{0.012}(a_{h\varepsilon}) + \underset{(0.001)}{0.002}(a_{k\varepsilon})], \tag{A.9b}$$

$$\hat{b}_L = D^{-1}[-\underset{(0.004)}{0.008}(a_{k\varepsilon}) + \underset{(0.005)}{0.010}(a_{h\varepsilon})]. \tag{A.9c}$$

While the unobservability of $a_{k\varepsilon}$ and $a_{h\varepsilon}$ preclude a definitive statistical conclusion, our results are strongly supportive of our conjecture that the estimation process would yield an upward bias on the physical and human capital coefficients and a downward bias on the labor coefficient. The first term in each expression of the predicted sign and statistically significant. While the second terms just miss being statisticallly significant at a 5% level, they are always close to significance and, more importantly, are of the proper sign.

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[22]For example, $a_{KL} = \sum_{i,t} T_{it}^{-2}(K_{i,t+T_{it}} - K_{i,t})(L_{i,t+T_{it}} - L_{i,t})$.

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