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Authors:

David E. Bloom, David Canning, and Jaypee Sevilla

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David E. Bloom[1], David Canning[2], and Jaypee Sevilla[3]

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[1] School of Public Health, Harvard University (email: dbloom@hsph.harvard.edu).
[2] Department of Economics, Queen's University of Belfast (email: d.canning@qub.ac.uk).
[3] School of Public Health, Harvard University (email: jsevilla@fas.harvard.edu).

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David E. Bloom	David Canning	Jaypee Sevilla
School of Public Health	Dept. of Economics	School of Public Health
Harvard Univ.	Queen's Univ. of Belfast	Harvard Univ.
dbloom@hsph.harvard.edu	d.canning@qub.ac.uk	jsevilla@fas.harvard.edu
617-432-0654	44-2890-273281	617-432-4054

Abstract

We estimate the contribution of human capital in the form of schooling, work experience, and health to the rate of growth of aggregate income. Our macro estimates for the effect of average schooling on aggregate output are consistent with micro estimates of the effects of individual schooling on earnings based on the Mincer earnings function, and suggest that there are no externalities to education. In addition, we find that improvements in health have a positive effect on aggregate output, which is again consistent with microeconomic findings of the effect of health status on wages. However, we find no evidence that increasing the average experience level of the workforce increases aggregate output. Overall, our result suggest the absence of large externalities and that calibrating growth models using microeconomic evidence on factor returns gives results that are compatible with the macroeconomic data.

Our estimates are based on estimating an aggregate production function. Two key issues when using this approach are the modeling of cross country differences in total factor productivity and dealing with reverse causality from output to factor inputs. We model steady-state total factor productivity in each country as depending on world technology and the country's geography and institutional structures. However, we find that a country's actual productivity level can be far from this steady state, and that countries converge towards their steady state productivity levels at a fairly slow rate. We identify the effect of inputs on output by assuming that while current inputs may depend on current output, and predicted productivity growth, they are uncorrelated with future productivity shocks.

1. Introduction

There is no doubt that labor quality in the form of human capital makes an important contribution to economic growth. However, most cross-country studies of this issue have focused fairly narrowly on the role of education. This is somewhat at odds with the microeconomic literature which takes a wider view of the concept of human capital; there is extensive evidence that earnings depend on work experience (e.g. see Mincer 1974) and health status (e.g. see Strauss and Thomas 1998), as well as years of schooling. We construct macro-economic measures of these variables to study to what extent the microeconomic evidence of their importance as forms of human carries over into their ability to explain economic growth. To investigate these issues we construct an aggregate production function in which output is determined by these labor and human capital inputs, as well as physical capital and total factor productivity. We then estimate this production function using panel data for the period 1960-1990.

One important issue in estimating such a production function is how to model total factor productivity, TFP. One approach is to take TFP levels to be the same in every country (e.g. see Mankiw, Romer, and Weil (1992)). However, it has been forcefully argued that there are persistent cross country differences in TFP levels and TFP growth (e.g. Prescott 1998, Temple (1999). We model these cross-country differences in TFP by assuming that that each country's TFP converges slowly towards its steady state level and that this steady state itself may vary across countries depending on their characteristics (such as geography and institutions) but grows over time with worldwide technical progress. This is really a model of slow technological diffusion, but with the possibility that countries have different steady state levels of TFP, which we find intrinsically appealing.

A second important issue is reverse causality. It seems likely that higher income leads to higher levels of invest in physical and human capital and may lead to better health (e.g. see Bils and Klenow (2000), Pritchett and Summers (1996)). We identify the effect of inputs on output by assuming that while current inputs may depend on current output, and predicted productivity growth, they are uncorrelated with future productivity shocks.

We estimate all the parameters in our model. An alternative approach is to calibrate the model using micro-economic evidence on parameter values (e.g. Young (1994, 1995) , Klenow and Rodriguez-Clare (1997), Prescott (1998)). The potential advantage of estimation using macro-data is our ability to pick up externalities that may only be apparent at the aggregate level.

Surprisingly, we find that our all our parameter estimates are very close to those found in microeconomic studies; indeed, the differences between our parameter estimates and the averages found in micro-studies are usually statistically insignificant. We find no evidence that there are positive externalities human capital in the form of schooling and experience (or that such externalities are too small for us to detect) and that calibration gives a good picture of the growth process. We find small but significant effects of health on human capital and output. In addition, we find constant returns to scale and that countries TFPs are converging towards their steady state levels at about 2.5% a year.

Section 2 describes our theoretical model and its properties. Section 3 describes our data set. Estimation results are reported and discussed in Section 4 and Section 5 gives our conclusions.

2. Theory

We assume that we can decompose economic growth into two sources: growth in the level of inputs and growth in total factor productivity (i.e. the efficiency with which those inputs are used).

While we wish to estimate the parameters of the production function directly from the data, we use factor share data and empirical results from labor economics to help us specify a functional form. The relative constancy of the shares of capital and labor in total income across the world suggests a Cobb-Douglas functional form for these inputs (though Duffy and Papageorgiou (2000) employ a more general function form).

For human capital the story is a little more difficult since we need to separate out the reward to human capital from the reward to raw labor in the wage bill. Unfortunately wage payments do not distinguish between these two rewards and so this is more than just an accounting issue. However, we have many microeconomic studies of the effect of human capital on wages, based on Mincer's (1974) pioneering work on human capital. This relationship, both theoretically and empirically, appears to have the following form:

$$\log w_j = \boldsymbol{a}_0 + \boldsymbol{a}_1 s_j + \boldsymbol{a}_2 \exp_j + \boldsymbol{a}_3 \exp_j^2 \qquad (1)$$

where w_j is the wage of individual j, s_j is his years of schooling, and exp_j is his years of experience. Note that the semi-log form of the relationship implies that the human capital variables exert a multiplicative rather than additive effect on wages. The marginal product of an extra year of schooling is $a_1 w_j$. The coefficient a_1 is therefore rate of return to schooling (assuming that the only cost of schooling are foregone earnings of student j). In this framework the rate of return to education is the same for each worker.

A simple decomposition of the wage bill in the U.S.A. using this approach gives about half the bill being a return to pure labor, a quarter being a return to education and the remaining quarter being a return to experience. This suggests that experience plays a large role in labor productivity and should be given roughly equal billing with schooling when we think about human capital. Bils and Klenow (1998) report estimates of this equation for 52 countries based on the work of Psacharopoulos (1994). Taking crude averages of the parameter estimates, we find a coefficient of 0.091 on schooling, 0.051 on experience and –0.0007 on experience squared. This implies that each year of education raises subsequent wages by about 9% while wages raise with experience at first but eventually fall, with the optimal level of experience being around 36 years.

Strauss and Thomas (1998) argue that good health is also associated with higher wages in micro-data and that we should regard health as a form of human capital. There is not yet a consensus on the magnitude of this health effect, but Strauss and Thomas report results which suggest that variations in wages for health reasons may be as least as great as those due to education. Health, in the form of life expectancy, has appeared in many gross country growth regressions and found to be significant but in these regressions it is unclear if health is beneficial to growth of if it is merely a proxy for other factors (e.g. see Barro and Sala-i-Martin (1995)). By including health in a well specified production function we hope to be able to isolate the effect of health on labor productivity.

We wish to estimate an aggregate production function that is compatible with the Mincer wage equation and compare the results with these micro-estimates. An analysis of the returns to education and experience reported in Bils and Klenow (1998) suggests that the rates of return are fairly constant across countries and do not vary systematically with national income level or average years of schooling of the workforce. This makes using a Cobb-Douglas production function including education problematic; with a Cobb-Douglas the rate of return to education (the marginal product of education divided by its cost, the output lost by withdrawing a worker from the labor force, that is, the marginal product of labor) falls one for one with average years of schooling of the workforce.

Instead we consider the aggregate production function

$$Y = AK^{\alpha}L^{\beta}e^{\phi_1 s + \phi_2 \exp + \phi_3 \exp^2 + \phi_4 h} \qquad (2)$$

where Y is total GDP, A represents TFP, K is the physical capital stock and L is the labor force. Human capital is modeled using s, the average years of schooling of the workforce, exp, the average experience level of the workforce, $\exp^2$ the average of experience squared (we square each workers experience before averaging), and h, the average level of health, which we proxy with life expectancy.

In this framework, the marginal product of a worker with average human capital is $b\,{}^{Y}\!/\!_{L}$ (this is the increase in output associated with an extra worker holding constant the average level of human capital, i.e. the extra worker is assumed to have the average level of human capital, which does not change). On the other hand the marginal product of extra year of education is $f_1\,{}^{Y}\!/\!_{L}$ (throughout we assume that all education takes place at the start of a worker's career so that the wage forgone has no experience component). It follows that, if we assume that the only cost of education is the lost output of the worker being educated, an extra year of education for an average worker has a social rate of return[4] of ${}^{f_1}\!/\!_{b}$. The intuition for this ratio is that the extra year of schooling adds proportionately to output, but its cost is wage forgone which depends on labor's share of output. Using this we can compare the results of estimating a production function like (2) with the rates of return found in (1). Similarly, ${}^{f_2}\!/\!_{b}$ and ${}^{f_3}\!/\!_{b}$ can be compared with the coefficients a_2 and a_3 in equation (1).

However, this analysis only gives the rate of social return for an average worker. We can calculate the social rate of return for a worker with s_j years of education as

$$\frac{f_1}{b + f_1(s_j - s)} \qquad (3)$$

[4] The social rate of return is sometimes used to denote the return to schooling in terms of wage premium relative to the cost of both student time and teaching inputs. Here we mean use it to mean increase in

which implies that different workers face different rates of return to education. This problem must occur in any model in which aggregate output depends only on average (or total) years of schooling since, in this case, the marginal benefit of a extra year of schooling is the same no matter who has it, while the cost in term of output forgone is lower for workers with low levels of education than for those with high levels of education. If we want to have an aggregate production function that preserves the Mincer equation property that the rate of return to education is constant across workers it needs to include the distribution, as well as the average level, of human capital.

In the interests of simplicity we assume only the total stock of education matters, not its distribution. We can, however, calculate the rate of return to a policy of increasing everyone's education level by the same amount and compare this with the microeconomic estimates from (1). Increasing everyone's education by the same amount has the marginal product $\boldsymbol{f}_1 Y$ while the wages forgone are $\sum_j (\boldsymbol{b} + \boldsymbol{f}_1(s_j - s))Y = \boldsymbol{b}Y$, so the rate of return to a policy of universal schooling is again $\boldsymbol{f}_1 / \boldsymbol{b}$.

It is worth comparing our approach with the "aggregate Mincer equation" methodology used by Heckman and Klenow (1997) and Krueger and Lindahl (2000). They argue that the social rate of return to education in (2) is simply $\boldsymbol{f}_1$ and it is this that should be compared with the rate of return estimates in micro equations. This is clearly inconsistent with our approach. We argue that the reason for the apparent inconsistency is that the "aggregate Mincer equation" approach implicitly assumes that the wage of a worker with no education is independent of the

aggregate output relative to the cost of student time, which is directly comparable to the estimates of the average level of education in the workforce. The production function we use implies that the wage of such a worker does depend on the other inputs in the economy, and in particular the average level of education, and so in our framework such an assumption would not be appropriate. This is discussed in detail in Appendix I.

Taking logs of the aggregate production function, we can derive an equation for the log of aggregate output in country i at time t

$$y_{it} = a_{it} + \alpha k_{it} + \beta l_{it} + \phi_1 s_{it} + \phi_2 \exp_{it} + \phi_3 \exp_{it}^2 + \phi_4 h_{it} \qquad (5)$$

where y_{it}, k_{it}, and l_{it} are the logs of Y_{it}, K_{it}, and L_{it} respectively. Equation (5) is an identity, but in practice a_{it}, the level of total factor productivity in country i at time t, is not observed and appears as an error term in the equation when we come to estimation.

The problem is, how are we to model this error term? One way to model this is to assume that the noise term in the production function contains a fixed effect, so that countries have different levels of TFP and these differentials are constant over time (e.g. Islam (1995), Caselli, Esquivel and Lefort (1996)). This implies that while countries have different levels of TFP the growth of rate of TFP is constant across countries. However, diffusion of technology might lead us to expect that while cross-country TFP levels do differ, they converge (slowly) over time.

This leads us to model TFP as following the process

$$a_{it} = a_{it}^{*} + v_{it} \text{ where } v_{it} = \rho v_{i,t-1} + \varepsilon_{it} \qquad (6)$$

private return in the literature which measure wage premium relative only to cost of student time.

where ε_{it} is a random shock. Each country has a long run steady state level of TFP given by a^*_{it}. One simple approach is to image that a^*_{it} is the same for every country so that $a^*_{it} = a_t$. In this case, v_{it} represents a country specific deviation from the common world technological level at time t. This deviation from steady state TFP levels may be persistent, but as time passes TFP levels converge the world TFP level at the rate $1 - \rho$. The speed at which TFP converges measures the speed of technological diffusion.

However, while technology may eventually diffuse, some countries may enjoy long run advantages in TFP that do not get eroded over time. For example, while technology may diffuse slowly as patent protection runs out, differences in institutional arrangements may persist unchanged throughout the time periods we consider. In addition, geographical factors may mean that some locations have productivity differentials, even in the long run. This suggests that we model long run TFP as $a^*_{it} = f(x_i) + a_t$ where x_i are country specific factors that may affect long run GDP. In practice, we use the percentage area in the tropics and a measure of institutional quality as factors that determine long run TFP levels.

For estimation purposes it is useful to turn our production function into a growth equation. Differencing equation (5) gives us

$$\Delta y_{it} = \Delta a_t + \alpha \Delta k_{it} + \beta \Delta l_{it} + \phi_1 \Delta s_{it} + \phi_2 \Delta \exp_{it} + \phi_3 \Delta \exp^2_{it} + \phi_4 h + \Delta v_{it} \quad (6)$$

Substituting out the error term using equation (6) and noting that the lagged productivity gap $v_{i,t-1}$ is the difference between actual output and output at the average world TFP level at time t-1 generates:

$$\Delta y_{it} = \Delta a_t + \alpha \Delta k_{it} + \beta \Delta l_{it} + \phi_1 \Delta s_{it} + \phi_2 \Delta \exp_{it} + \phi_3 \Delta \exp_{it}^2 + \phi_4 \Delta h_{it} \qquad (7)$$

$$+ (1-\rho)(a_{i,t-1} + \alpha k_{i,t-1} + \beta l_{i,t-1} + \phi_1 s_{i,t-1} + \phi_2 \exp_{i,t-1} + \phi_3 \exp_{i,t-1}^2 + \phi_4 h_{i,t-1} - y_{i,t}) + \varepsilon_{it}$$

Growth in output can be decomposed into four components. The first is the growth of world total factor productivity. The second is the growth of inputs. The third a catch-up term as some of the country's TFP gap, $v_{i,t-1}$, is closed and the country converges, at the rate $1-\rho$, to its steady state level of TFP. Finally there is an idiosyncratic shock to the country's TFP, ε_{it}.

Equation (7) has an interesting special case. If $\rho = 1$, so that all all shocks to TFP are permanent, the lagged level terms in (7) dissappear. Our approach therefore encompases the estimation of the prodcution function in first differences as advocated by Pritchett (1999), and Krueger and Lindahl (2000) and we can test if this restriction holds. It is worth noting that in our framework the speed of convergence, $1-\rho$, is the rate at which TFP is converging. This is is sharp contrast with models (such as Mankiw, Romer, and Weil (1992)) where the capital and human capital stocks are repaced with their long run steady states based on current investment levels. In thse models, TFP is constant across countries and the speed of convergence refers to the time period it takes for investment to accumulate and for capital stocks to reach their steady state levels.

The problem with using contemporaneous input growth rates is of course that these are very likely to be endogenous and responsive to the current TFP shock, $e_{i,t}$. We overcome this problem by instrumenting these current input growth rates with lagged input growth rates. We assume that these lagged input growth rates and the lagged levels of inputs are uncorrolated with $e_{i,t}$, the current *shock* to TFP. This is quite compatible with lagged TFP levels and *expected* TFP growth (the catchup term in equation 7) affecting previous input decisions. The argument that the lagged input levels are uncorrolated with the current shock to TFP is the real rationale for estimating (7) rather than the level relationship in (5). If we were to estimate the level realtionship there would be serious worry that the current input levels were correlated with the current level of TFP (which, after all, affects output and the pool of resources available for investment). In the levels equation, using lagged input levels as instruments is not appropriate because the autocorrelation in TFP over time means that lagged input levels can be correlated with lagged TFP levels which in turn are correlated with current TFP levels.

An important implication of our model is that the coefficients on a lagged input level and its current growth rate should be the same. When we came to estimation we can test this restiction as a simple check on our models assumptions. Failure to satisfy these equality restricions would point towards a more complex error structure for TFP.

3. Data

We construct a panel of countries observed every ten years from 1960 to 1990. Output data (GDP) is obtained from the Penn World Tables version 5.6 (see Summers and

Heston (1991) for a description). We obtain total output by multiplying the real per capita GDP measured in 1985 international purchasing power parity dollars (chain index), by national population.

Data on economically active population are from the International Labor Organization (1997). This also gives labor force participation rates for men and women separately, by five-year age cohorts. Our labor supply is given by their estimates of the total economically active population in the given year. However, this measure is unable to adjust for the fact that some fraction of the labor force is unemployed and therefore should not be counted as providing labor inputs. Nor are we able to adjust for the hours worked of the labor force. Schooling is measured by the average total years of schooling of the population aged 15 plus from Barro-Lee (2000).

Life expectancy data is from the United Nations (1998). We use this as a proxy for the health of the workforce, even though it measures mortality rates rather than morbidity. Higher life expectancy is generally though to be associated with better health status and lower morbidity (Murray and Chen (1992), Murray and Lopez (1997)).

We construct aggregate experience for each country by computing an experience measure for 22 gender/age group combinations (male and female versus age groups 15-19, 20-24,...,60-64, 65+). Experience for each group is given by average age, minus average years of schooling, minus six. This measure of experience is likely to be reasonable for males but may overstate the experience of females who more frequently spend periods out of the labor market. For simplicity in our calculations, the average age in each group is taken to be the mid point of its age range. Average experience in the workforce is formed by using shares of each group in the total economically active population. Aggregate squared experience is the weighted average of the squared experience of each group.

In this calculation of experience, measured years of schooling for groups aged 25 and more differ by gender but are assumed constant across age groups within each gender. They are set to Barro-Lee measures of total schooling for the male and female populations aged over 25. Years of schooling for the groups aged 15-19, and 20-24 are calculated by combining Barro-Lee data on schooling for populations aged 15 or more and 25 or more to infer education for the population aged 15-24 using the fact that schooling for the population aged over 15 equals the weighted average of schooling for the 15-24 population and schooling for the population aged more than 25 where the weights are population shares.

Our capital stock series for each country is computed by a perpetual inventory method. We initialize the capital series in the first year for which there is investment data in the Penn World Tables (version 5.6), setting it equal to the average investment/GDP ratio in the first five years of data, multiplied by the level of GDP in the initializing period, and divided by .07, our assumed depreciation rate. This is the capital stock we would expect in the initial year if the investment/GDP ratio we use is representative of previous rates. Each succeeding period's capital is given by current capital minus depreciation at 7%, plus the level of current investment.

Our capital stock series has wider coverage than Summers-Heston variable for capital stock per worker, kapw, which is only available for 62 countries from 1965 onwards. Where the two overlap, the correlation coefficient between the log levels of our series and theirs is 0.97, indicating that the two series are very similar. For many countries investment series do not start until 1960 suggesting that our capital stock data for the 1960's may be suspect because of the way we construct the initial stock of capital. Because of depreciation, by 1970 the capital stock estimates become fairly independent of the initializing assumption used; we therefore limit our estimation to the period 1970-1990, though data from the period 1960-1970 are used as instruments.

Our measure of institutional quality is the good governance variable from Knack and Keifer (1995), while percentage of land area in the tropics comes from Gallup, Sachs and Mellinger (1999).

4. Estimation and Results

We begin by estimating equation (7) under the assumption that steady state TFP levels are the same in every country; the results are reported in table 1. Each regression is estimated by nonlinear least squares, and all contemporaneous growth rates of inputs are instrumented with their lagged growth rates. Time dummies (not reported) are included which proxy the average level of total factor productivity in each period; these appear in levels in the "catch up" part of the regression, while the differences between successive time periods measures growth in average total factor productivity over the period.

In Column (1) of Table 1 we report results where we include only physical capital, human capital and labor as inputs. We find coefficients of close to 1/2 each on capital and labor, which seems a little high on capital compared to the evidence of its share of income. The sum of these coefficients on labor and capital is close to one and we cannot reject the restriction of constant returns to scale. Our estimate of the coefficient on schooling translates into a social rate of return of 17.2% which is somewhat higher than the average of 9.1% found in micro studies. However, while we find that this estimated rate of return to schooling is significantly different from zero, it is not very well determined and we cannot reject the hypothesis that that it is the same as the micro-estimate of 9.1%. The catch-up coefficient is 0.196, indicating that almost 20% of the TFP gap at the start of the decade is closed up after ten years; that is, TFP levels are converging at a rate of about 2% a year.

Adding our experience variables in column (2) has the effect that none of our human capital coefficients is now significant. However, when we calculate the rate of return to schooling we get a figure of 12.8%, which is statistically different from zero though we again cannot reject the hypothesis that the actual rate of return is 9.1%. The coefficients on average experience and average experience squared are very large in absolute size though poorly determined. We cannot reject that these coefficients are jointly zero (or indeed that they produce estimates of the productivity of experience that are the same as those found in the micro studies).

The reason for the poorly determined coefficients on our experience measures seems to be that in our sample the average experience and the average of experience squared are very highly correlated (the correlation coefficient is above 0.98). Average experience in our sample ranges from 18 to 28 years, and over this short range its relationship with the average of experience squared that is almost completely linear.[5] The problem is that while the wide range of years of work experience we see in micro-data allows us to identify the non linear

[5] In fact, the average of experience squared can be written as the square of average experience plus the variance of experience across individuals within the country. This implies that it is not only the lack of variation in average experience that is the problem; in addition, the variance of experience across the workforce is similar across countries.

relationship between experience and wages, in macro data the very small variation in average experience across countries means we cannot pick up such subtle effects.

Adding life expectancy in column (3) gives similar results. Again, the human capital measures collectively have a non-zero impact but we cannot reject the hypothesis that the coefficients are equal to those found in micro-studies. The coefficient on life expectancy is 0.01 suggesting that increasing life expectancy by one year improves workforce health and raises output by about 1%, though this effect is not well determined and the coefficient is not statistically significant. It is notable in column (3) of table 1 that the coefficients on capital and labor take on values that are very close to their stylized factor shares of 1/3 and 2/3.

In all three regressions in table 1 we cannot reject the hypothesis that we have constant returns to scale; that is, that the coefficients on physical capital and labor add to one. In addition, in each regression we cannot reject the restriction the coefficients on the levels and growth rates of inputs are equal.

We do not report or estimates of the world technology levels; in fact these are not fully identified. We can estimate for each period the total technology effect (the sum of the world rise in the level of technology, plus the convergence effect as countries catch up with the base year's world technology level). However, we cannot separate these two effects out without imposing additional restrictions. The problem is that if we see very fast growth in a particular period, we cannot say if it because the base year TFP level was high, and all countries are converging towards this, or because during the period world TFP has grown quickly.[6]

[6] One additional restriction would identify TFP in the model. For example, we might fix world benchmark TFP in 1960 as the TFP of the USA (i.e. set 1960 world TFP so that the error term for the USA in that year is zero),

Overall, the picture that emerges from table 1 is that the macro-results are surprisingly close to the results found in microeconomic studies. We find in every case that we cannot reject the hypothesis that the macroeconomic estimates on the returns to schooling and experience are the same as the microeconomic evidence. In all specifications we have appear to constant returns to scale, though in some the coefficient on physical capital appears to be closer to ½ rather than the 1/3 that seems to be the stylized fact from factor share data. There are large gaps in total factor productivity across countries but these gaps are being closed at the rate of about 2% a year.

The results in table 1 may depend on our assumption that the steady state level of TFP is the same in every country. We experimented with different geographical and institutional variables that may explain long run differences in TFP and settled on percentage of land area in the tropics and our governance measure as the two that seem most significant in our framework. We include these variables (which are taken as fixed over time) in the levels part of equation (7).

In addition, in table 2 we exclude average experience squared from the estimation. When we included the squared term, we found that, as in table 1, the estimates of the coefficients on the two experience variables were very poorly determined. Giver the short range of average experience levels in the sample we estimate a linear experience effect rather than a nonlinear effect. The average experience level in our sample is 23 years, and at this experience level the marginal impact of an extra year of experience on wages (using our micro-data

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or as world average TFP (so that the average of the error terms in 1960 is zero). However, the normalization we use does affect the estimates of both the level and growth rate of world technology.

coefficients) should be about 1.8% and the expected effect on output (assuming no externalities) is therefore just $(1.8 \times \boldsymbol{b})$ % implying a coefficient on experience in our regressions of around 0.01.

In all columns of table 2 we find that the coefficient on schooling is small and not statistically significant. However, we cannot reject that the rate of return to schooling is 0.091 as given by micro-economic data. Adding average experience in columns (2) and (3) generates coefficients on experience that are negative and lower than the productivity effects found in microeconomic studies. This suggests that experience reduces aggregate output, even though in microeconomic data it increases individual wages.

Adding life expectancy in column 3 produces a result that is positive and statistically significant and suggests that each extra year of life expectancy rises the health of workers and leads to an increase of 4% in output. This is quite a large effect, indicating that increased expenditures on improving health might be justified purely on the grounds of their impact on labor productivity.

As we would expect, countries with better governance tend to have higher steady state levels of TFP while those in the tropics have lower TFP. The speed of TFP convergence is again around 2%-2.5% a year.

While our results generally agree with those found in micro-studies our parameters estimates are not well determined. For example, in column 3 of table 2 even the coefficient on physical capital is not statistically significant. A central problem in macroeconomic studies is a lack of degrees of freedom. In addition, there is a great deal of multicollinearity in aggregate data; capital intensity, education level, health status, all tend to move together. As we have seen average experience and average experience squared are highly correlated, while average experience is highly negatively correlated with average schooling (extra years of education mean less average experience over one's working life).

Determining the rates of return to inputs from macro-data with any precision is likely to be difficult. This suggests that so long as the aggregate data does not suggest the presence of large externalities, we should calibrate macro-models using estimates of private returns from micro studies.

5. Conclusion

Our model accounts for economic growth by the growth of factor inputs, technological innovation and technological diffusion. We find no evidence that the macro-economic effects of education and experience are any greater to those found in micro studies. This suggests the absence of externalities at the aggregate level and that calibration studies provide reasonable pictures of the proximate sources of economic growth. We do find evidence of a positive effect of health on productivity, which again is consistent with the microeconomic evidence.

Accounting for economic growth is only the first stage of an explanation. Once we have established the importance of physical and human capital we need to go behind these variables to ask what determines cross-country differences in factor accumulation. For example, our estimates of the effect of life expectancy capture only its direct effect on the productivity of labor. In a fully specified model life expectancy may influence life cycle savings (Lee, Mason and Miller (2000)) and capital accumulation, and the expected returns to, and investment in education (Bils and Klenow(2000)). It follows that improvements in health may increase output not only through labor productivity but also through the accumulation of capital. A fully specified model of economic growth would be multi-dimensional, showing not only how inputs and technology affect output, but how the growth rates of inputs and technological are themselves determined.

Bibliography

Barro, R. and Lee, J. 2000, "International Data on Educational Attainment: Updates and Implications," Center for International Development, Working Paper No. 42, Harvard University.

Barro, R. and Sala-I-Martin, X., 1995, *Economic Growth,* New York, McGraw-Hill.

Benhabib, J. and Spiegel, M., 1994, "The Role of Human of Capital in Economic Development: Evidence from Aggregate Cross-Country Data," *Journal of Monetary Economics*, Vol. 34, pp 143-74.

Bils, M. and Klenow, P., 2000, "Does Schooling Cause Growth?" *American Economic Review*, Vol. 90, pp 1160-83.

Caselli F., Esquivel G. and Lefort F., 1996, "Reopening the Convergence Debate: A New Look at Cross Country Growth Empirics," *Journal of Economic Growth*, Vol. 1, pp 363-389.

Duffy J. and Papageorgiou C., 2000, "A Cross-Country Empirical Investigation of the Aggregate Production Function Specification," *Journal of Economic Growth*, Vol. 5, pp 87-120.

Gallup J.L., Sachs J.D., and Mellinger A. (1999), "Geography and Economic Development," International Regional Science Review, Vol. 22, pp 179-232.

Hall, R., and Jones, C., 1996, "The Productivity of Nations," NBER Working Paper No. 5812.

Heckman, J. and Klenow, P. 1997. Human Capital Policy. Mimeo.

Heston, A. and Summers, R., 1994, *Penn World Tables v5.6*. Revision of Heston, A. and Summers, R., 1991, "The Penn World Table (Mark 5): An Expanded Set of International Comparisons, 1950-1988," *Quarterly Journal of Economics*, Vol. 106, pp 327-68.

International Labor Office, 1997, *Economically Active Population, 1950-2010*, Geneva, International Labor Office.

Islam N., 1995, "Growth Empirics: A Panel Data Approach," *Quarterly Journal of Economics*, Vol. 110, pp 1127-70.

Klenow P.J. and Rodriguez-Clare A., 1997, "The Neoclassical Revival in Growth Economics: Has it Gone Too Far?" in Bernanke, B. and Rotemberg, J. eds., *NBER Macroeconomics Annual*, Cambridge, MA, MIT Press.

Knack S. and Kiefer P., 1995, "Institutions and Economic Performance: Cross-Country Tests Using Alternative Institutional Measures," *Economics and Politics*, Vol. 7, pp. 207-227.

Krueger, A. and Lindahl, M., 2000, "Education for Growth: Why and for Whom?" NBER Working Paper, No. 7591.

Lee R. Mason A. and Miller T., 2000, "Life Cycle Saving and the Demographic Transition: the Case of Taiwan," *Population and Development Review*, Vol. 26, supp. pp 194-222.

Mankiw N.G., 1997, "Comment on Klenow and Rodriguez-Clare," In Bernanke, B. and Rotemberg, J. eds., *NBER Macroeconomics Annual*, Cambridge, MA, MIT Press.

Mankiw, N.G., Romer, D., and Weil, D., 1992, "A Contribution to the Empirics of Economic Growth," *Quarterly Journal of Economics*, Vol. 107, pp 407-37.

Mincer, J., 1974, *Schooling, Earnings, and Experience*, New York, Columbia University Press.

Murray C.J.L. and Chen L.C., 1992, "Understanding Morbidity Change," Population and Development Review, Vol. 18, pp 481-503.

Murray C.J.l. and Lopez A.D., 1997, "Regional Patterns of Disability-Free Life Expectancy, and Disability Adjusted Life Expectancy: Global Burden of Disease Study," *Lancet*, Vol. 349, pp 1347-1252.

Prescott, E. C., 1998, "Needed: A Theory of Total Factor Productivity," *International Economic Review,* Vol. 39, pp. 525-51.

Pritchett, L., 1999, "Where Has All the Education Gone?" World Bank Policy Research Paper, No. 1581.

Pritchett, L. and Summers, L. 1996, "Wealthier is Healthier," *Journal of Human Resources*, Vol. 31, pp 844-68.

Psacharopoulos G., 1994, "Returns to Investment in Education: A Global Update," *World Development*, Vol. 22, pp. 1325-1343.

Strauss J. and Thomas D. (1998), "Health, Nutrition and Economic Development," *Journal of Economic Literature*, Vol. 36, pp 766-817.

United Nations, 1996, *Demographic Indicators 1950-2050,* New York: United Nations.

United Nations, 1998, *Demographic Indicators 1950-2050,* New York: United Nations.

Young, A., 1994, "Lessons from the East Asian NIC's: A Contrarian View," *European Economic Review*, Vol. 38, pp. 964-973.

Young, A., 1995, "The Tyranny of Numbers: Confronting the Statistical Realities of the East Asian Growth Experience," *Quarterly Journal of Economics*, Vol. 110, pp. 641-680.

Appendix I

Heckman and Klenow (1997) and Krueger and Lindahl (2000) derive their result by arguing that we can average equation (1) over workers. This gives a figure for the average of log wages. However, if we assume that the distribution of wages is lognormal the log of average wages is equal to the log of the median wage plus half the variance of wages (Hastings and Peacock (1975)). But, for a lognormal distribution, the log of the median wages equals the average of log wages (since log wages have a symmetrical distribution). Hence

$$\log \bar{w} = \overline{\log w} + \frac{1}{2}\sigma^2 = \alpha_0 + \frac{1}{2}\sigma^2 + \alpha_1 \bar{s} + \alpha_2 \overline{\exp} + \alpha_3 \overline{\exp^2} \qquad \text{(A1)}$$

where σ is the standard deviation of log wages. Now if we assume that workers are paid their marginal products, from our aggregate production function (ignoring for the moment health effects) we can calculate the marginal product of workers with each level of human capital and then add over workers to give

$$\log \bar{w} = \log \beta \frac{Y}{L}$$
$$= \log \beta + \log A + \alpha \log(K/L) + (\alpha + \beta - 1)\log L + \phi_1 \bar{s} + \phi_2 \overline{\exp} + \phi_3 \overline{\exp^2} \qquad \text{(A2)}$$

This appears to be consistent with the aggregated Mincer equation (equation (A1) above) where the intercept of the wage equation varies across countries due to differences in total factor productivity A, capital per worker K/L, and a scale effect that depends on the size of the labor force (note that this dependence on L disappears if we have constant returns to scale, so that $\alpha + \beta = 1$). It is now tempting to compare (A1) and (A2) and argue that the parameters on education in the micro and macro equations can be compared directly so that ϕ_1 must be the return to education. However, this is not so.

The flaw in the argument is that when we aggregate the Mincer equation in (A1) we implicitly assumed that a_0 was a constant, independent of the average level of education. But from equation (1) it is clear that a_0 is the log wage of a worker with no education and no experience. While this can be regarded as fixed in a microeconomic study within a country, with our production function the wage of such a worker does depend on the average level of education. For example, assuming our production function (2) holds, and taking the simple case where A, K and L are normalized to 1 and experience has no effect on productivity, and setting the wage of a worker with education equal to his marginal product, we have

$$a_0 = \log w_0 = \log(b - f_1 s)\frac{Y}{L} = \log(b - f_1 s) + f_1 s \quad \text{(A3)}$$

This clearly implies that the wage earned by an uneducated worker depends on the average stock of education.[7] Given our production function there is a fallacy of aggregation in (A2) the parameter a_0 is not a constant but should be written as a function of the average level of each of our human capital variables. The parameter on average years of schooling in the aggregate equation is the sum of the individual effects as in A1 *plus* its effect on the wage of an uneducated worker, a_0. The "aggregate Mincer equation" is only valid if a_0, is the same across countries and does not itself depend on the average education level, which would require a production function somewhat different from ours.

[7] Note that this formula holds for low levels of average education. If average education levels are high enough the marginal product of an uneducated worker may be negative (his negative impact in lowering the average years of schooling outweighs the pure effect of his labor supply) and he should not be employed.

Table 1

Production Function in Growth Form Common Long Run TFP Across Countries Dependent Variable: Growth rate of GDP Nonlinear two stage least squares			
	1	2	3
Capital	0.522* (0.067)	0.424* (0.094)	0.342* (0.116)
Labor	0.493* (0.080)	0.633* (0.121)	0.708* (0.136)
Schooling	0.085* (0.039)	0.081 (0.048)	0.082 (0.049)
Experience		0.208 (0.176)	0.266 (0.203)
Experience^2		-0.0045 (0.0029)	-0.005 (0.003)
Life Expectancy			0.013 (0.011)
Technological Catch-up Coefficient	0.196* (0.040)	0.191* (0.041)	0.214* (0.043)
N	175	175	175
R^2 adjusted	0.628	0.581	0.549
Test of equality of growth and level coefficients (chi-square d.o.f. under null)	4.15 (3)	2.66 (5)	0.93 (6)
Estimate of the rate of return to schooling	0.172* (0.062)	0.128* (0.063)	0.116 (0.060)
Test that rate of return to schooling equals 0.091 (chi-square d.o.f. under null)	1.66 (1)	0.34 (1)	0.18 (1)
Test of zero coefficients on experience (chi-square d.o.f. under null)		4.39 (2)	4.00 (2)
Test of constant returns to scale (chi-square d.o.f. under null)	0.13 (1)	1.19 (1)	1.09 (1)

Estimated on a panel of 104 countries for the growth periods 1970-1980 and 1980-1990.

Year dummies are included throughout.
* denotes significance at the 5% level.

Table 2

Production Function in Growth Form **Country Specific Long Run TFP** Dependent Variable: Growth rate of GDP Nonlinear two stage least squares			
	1	2	3
Capital	0.457* (0.065)	0.479* (0.068)	0.190 (0.151)
Labor	0.583* (0.085)	0.589* (0.088)	0.824* (0.145)
Schooling	0.015 (0.038)	-0.026 (0.045)	-0.025 (0.043)
Experience		-0.074* (0.034)	-0.059 (0.036)
Life Expectancy			0.040* (0.019)
Technological Catch-up Coefficient	0.186* (0.039)	0.194* (0.042)	0.278* (0.045)
Percent Land Area in the Tropics	-0.432* (0.207)	-0.329 (0.204)	-0.332* (0.161)
Governance	0.098* (0.045)	0.104* (0.047)	0.149* (0.050)
N	147	147	147
R^2 adjusted	0.711	0.679	0.539
Test of equality of growth and level coefficients (chi-square d.o.f. under null)	1.901 (3)	1.069 (4)	2.764 (5)
Estimate of the rate of return to schooling	0.026 (0.064)	-0.044 (0.079)	-0.030 (0.053)
Test that rate of return to schooling equals 0.091 (chi-square d.o.f. under null)	0.663 (1)	2.920 (1)	5.215* (1)
Test of constant returns to scale (chi-square d.o.f. under null)	1.018 (1)	1.532 (1)	0.092 (1)

Year dummies are included throughout.
* denotes significance at the 5% level.