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THE EFFECT OF HEALTH ON ECONOMIC GROWTH: THEORY AND EVIDENCE

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ABSTRACT

Macroeconomists acknowledge the contribution of human capital to economic growth, but their empirical studies define human capital solely in terms of schooling. In this paper, we extend production function models of economic growth to account for two additional variables that microeconomists have identified as fundamental components of human capital: work experience and health. Our main result is that good health has a positive, sizable, and statistically significant effect on aggregate output. We find little variation across countries in average work experience, thus differentials in work experience account for little variation in rates of economic growth. Finally, we find that the effects of average schooling on national output are consistent with microeconomic estimates of the effects of individual schooling on earnings, suggesting that education creates no discernible externalities.

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1. Introduction

Although labor quality in the form of human capital clearly contributes significantly to economic growth, most cross-country empirical studies identify labor quality narrowly with education. Our central argument is that this practice ignores strong reasons for considering health to be a crucial aspect of human capital, and therefore a critical ingredient of economic growth. Healthier workers are physically and mentally more energetic and robust. They are more productive and earn higher wages. They are also less likely to be absent from work because of illness (or illness in their family). Illness and disability reduce hourly wages substantially, with the effect especially strong in developing countries, where a higher proportion of the work force is engaged in manual labor than in industrial countries. A substantial body of microeconomic evidence documents many of these effects (see Strauss and Thomas 1998). Testing whether such effects translate into an aggregate effect of population health on economic growth is important. Health, in the form of life expectancy, has appeared in many cross-country growth regressions, and investigators generally find that it has a significant positive effect on the rate of economic growth (see Bloom and Canning 2000, 2001). However, these regressions do not clearly indicate whether health directly benefits growth or whether it is merely a proxy for other missing or mismeasured factors (see, for example, Barro and Sala-I-Martin 1995).

The main objective of this study is to include health in a well-specified aggregate production function in an attempt to test for the existence of a true effect of health on labor productivity, and to measure its strength. However, because human capital is multidimensional, we need a model of growth that includes all its major components. This ensures that we do not erroneously overestimate the contribution of one component by mistakenly attributing to it the contributions of those components we omit. Thus we further add work experience to our model, because considerable microeconomic evidence indicates that it has an impact on workers' earnings (see, for example, Mincer 1974). We construct macroeconomic measures of health and work experience to examine whether microeconomic evidence of their importance as forms of human capital carries over into their ability to explain economic growth.

To this end we construct an aggregate production function that expresses a nation's output as a function of its inputs and the efficiency with which it uses these inputs. These inputs are physical capital, labor, and human capital in the three dimensions of education, experience, and health. Our model also considers the efficiency with which these inputs are used, that is, total factor productivity (TFP). We estimate all the parameters of this production function using panel data for 1960-90 and obtain measures of the relative contributions of each of the inputs and of TFP to economic growth.

An alternative approach is to calibrate the model using microeconomic evidence for parameter values (see, for instance, Klenow and Rodriguez-Clare 1997; Prescott 1998; Young 1994, 1995). The potential advantage of estimation over calibration is that the microeconomic evidence measures the effect of improvements in an individual's human capital on own earnings, ignoring the additional effects it might have on other individuals or on society as a whole. These additional effects, that is, externalities, might arise because people's productivity depends on the productivity of their coworkers. When workers obtain more schooling, their earnings rise, but those of their coworkers may rise as well. By estimating the returns to human capital in aggregate, we let these returns differ from microeconomic estimates, which allows us to make inferences about the existence and magnitude of the externalities.

Our main result is that health has a positive and statistically significant effect on economic growth. It suggests that a one year improvement in a population's life expectancy contributes to a 4 percent increase in output.

We also find that our estimates of the contributions of education and work experience are close to those found in microeconomic studies. Indeed, the differences between our parameter estimates and the averages found in microeconomic studies are usually statistically insignificant. Thus we find no evidence of the existence of externalities to human capital in the form of schooling and experience (or such externalities are too small for us to detect). While large cross-country differences in life expectancy and average years of schooling explain a substantial proportion of the income gaps we observe between countries, cross-country differences in average work experience are small, implying that work experience plays a relatively minor role in explaining income gaps.

2. Theory

We assume that we can decompose economic growth into two sources: growth in the level of inputs and growth in TFP. We take our inputs to be physical capital, labor, and human capital.

We model output as a function of inputs and technology using the following aggregate production function:

$$Y = AK^{\alpha} L^{\beta} e^{\phi_1 s + \phi_2 \exp + \phi_3 \exp^2 + \phi_4 h}, \qquad (1)$$

where Y is output or gross domestic product (GDP); A represents TFP; K is physical capital; L is the labor force; and human capital consists of three components, average years of schooling s, average work experience of the work force $\exp$, average square of work experience $\exp^2$, and health h (which we proxy with life expectancy). We express the effect of the human capital terms on output as powers of an exponential. As long as workers earn their marginal product, using this functional form implies that log wages depend on the level of schooling, experience, experience squared, and health status, which is the relationship usually found in microeconomic studies.

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

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

where $y_{it}, k_{it},$ and l_{it} it are the logs of $Y_{it}, K_{it},$ and L_{it}, respectively. Equation (2) is an identity, but in practice a_{it}, the level of TFP in country i at time t, is not observed and appears as an error term when the equation is estimated.

We model TFP as follows:

$$a_{it} = a_{it}^{*} + v_{it}\text{, where } v_{it} = \rho v_{i,t-1} + \varepsilon_{it}, \qquad (3)$$

where $0 < \rho < 1$ and ε_{it} is a random shock. Each country has a long–run, steady-state level of TFP given by a_{it}^{*}. Its actual TFP, given by a_{it}, deviates from the steady state by the random difference v_{it}, which consists of systematic and idiosyncratic components. The systematic difference, represented by ρv_{it-1}, shrinks over time. The idiosyncratic randomness is represented by ε_{it}. A simple special case popular in the literature (see, for example, Mankiw, Romer, and Weil 1992) is to posit that a_{it}^{*} is the same for every country, so that $a_{it}^{*} = a_{t}^{*}$. In this case, v_{it} represents country i's deviation from the world's common level of technology at time t. This deviation may be persistent, but as time passes, this country's TFP converges to the world level at the rate $1-\rho$, which represents the speed of technological diffusion.

While technology may eventually diffuse, some countries may enjoy long-run advantages in TFP that are not eroded over time, so that $a^{*}_{it} \neq a_{t}^{*}$. To parsimoniously model how steady-state TFP may differ across countries, we allow a_{it}^{*} to be a function of geography, proxied by the percentage of country i's area that is in the tropics, and a measure of the quality of its political institutions. Tropical location has recently been viewed as a geographical disadvantage to growth because of obstacles it creates in the diffusion of agricultural technologies from temperate to tropical zones, disadvantages in food production, and infectious disease ecology (see Bloom and Sachs 1998). The quality of political institutions, on the other hand, has been argued to affect economic growth because it provides the social stability, effective provision of public services, and enforcement of private contracts that are required for growth.

For estimation purposes, turning our production function into a growth equation is useful. Differencing equation (2) gives us

$$\Delta y_{it} = \Delta a_t + \alpha \Delta k_{it} + \beta \Delta l_{it} + \phi_1 \Delta s_{it} + \phi_2 \Delta \exp_{it} + \phi_3 \Delta \exp_{it}^2 + \phi_4 \Delta h_{it} + \Delta v_{it} . \qquad (4)$$

Substituting out the error term Δv_{it} using equation (3) and noting that the lagged productivity gap v_{it-1} is the difference between actual output and output at the average world TFP level at time $t-1$ generates

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

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

Equation (5) shows that growth in output can be decomposed into four components: the growth of world TFP; the growth of inputs; a catch-up term as some of the country's TFP gap, v_{it-1}, is closed and the country converges to its steady-state level of TFP at the rate $1-\rho$,; and an idiosyncratic shock to the country's TFP, ε_{it}.

The problem with estimating equation (5) as it stands is reverse causality. While we are interested in measuring the contribution of input growth to output growth, output growth may have a reverse causal effect on input growth. For example, economic growth may stimulate investments in physical capital. Output growth may also augment human capital by facilitating increased schooling or improving people's health (see, for example, Bils and Klenow 2000; Pritchett and Summers 1996). Statistically speaking, this reverse causality creates a correlation between the input growth (independent) variables and the error term ε_{it} that renders ordinary least squares estimates of the coefficients in equation (5) inconsistent.

Consider a country that experiences an unforeseen and idiosyncratic improvement in efficiency, $\varepsilon_{it} > 0$, that raises output, and therefore also raises inputs through the mechanisms just explained. We would observe growth in both outputs and inputs, yet incorrectly attribute the growth in outputs to growth in inputs, when in reality the relationship is exactly the reverse. This would lead us to overstate the contribution of inputs to growth. We need to disentangle the effect of inputs on growth from the effect that growth has on inputs. We accomplish this by using an instrumental variables (IVs) technique. An IV is a variable that must satisfy two criteria. First, it must be correlated with the endogenous independent variables, that is, the variables that suffer from reverse causation. In our case, these endogenous variables are the input growth rates in equation (5). Second, it must be uncorrelated with the error term ε_{it}, conditional on the IV's correlation with every other specified independent variable on the right-hand-side of equation (5). Intuitively, this second requirement implies that the IV must be uncorrelated with any random TFP shocks that might provoke the reverse causal mechanism described earlier. If such an IV exists, then the first condition ensures that variations in the IV induce variations in the endogenous inputs. The second condition ensures that the reverse causality problem will not contaminate these induced variations in the endogenous inputs. Thus correlations between variations in output and the induced variations in the endogenous inputs can be interpreted as the causal effect of input growth on output growth, disentangled from the reverse causality problem.

We assume that lagged levels and growth rates of inputs serve as valid IVs. These clearly satisfy the first condition: lagged input use is a good predictor of current input use. It also arguably satisfies the second condition. While lagged input use probably correlates with predictable changes in the efficiency with which a nation uses its inputs, it is unlikely to be related to unpredictable changes in this efficiency, represented by the idiosyncratic error term ε_{it}. Assuming lagged inputs satisfy the two conditions is quite compatible with lagged TFP levels and expected TFP growth (the catch-up term in equation [5]) affecting previous input decisions. An important implication of our model is that the coefficients on a lagged input level and its current growth rate should be the same. We test this restiction as a simple check on our model's assumptions. Failure to satisfy these equality restrictions would point toward a more complex error structure for TFP.

3. Data

We construct a panel of countries observed every 10 years from 1960 to 1990. Output data (GDP) are obtained from the Penn World Tables (see Heston and Summers 1994 for a description). We obtain total output by multiplying real per capita GDP measured in 1985 international purchasing power parity dollars (chain index) by national population.

We measure a country's labor supply by the size of its economically active population using data from the International Labour Office (1997), which also gives labor force participation rates disaggregated by gender and five-year age groups. However, our labor supply 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 the labor force works. Schooling is mea sured by the average total years of schooling of the population aged 15 years and older from Barro and Lee (2000).

Life expectancy data are from the United Nations (1998). We use these as a proxy for the health of the work force, even though they measure mortality rates rather than morbidity. Higher life expectancy is generally thought to be associated with better health status and lower morbidity (Murray and Chen 1992; Murray and Lopez 1997).

We construct a measure of aggregate work experience for each country by computing an experience measure for each of 22 gender and age group combinations (male and female for age groups 15-19, 20-24,...,60-64, 65+). Experience is simply the amount of time spent in the labor force. For each group we measure this by average age minus average years of schooling minus the age at which schooling starts, which we uniformly assume to be 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, we take the average age of each group to be the mid-point of its age range. Average work force experience for the country as a whole is a weighted average of the group-specific experience measures, where the weights are the shares of each group in the total economically active population. Aggregate squared experience is the analogous weighted average of the squared experience of each group.

In this calculation of experience, measured years of schooling for groups aged 25 and older differ by gender, but are assumed to be constant across age groups within each gender. They are set to Barro and Lee's (2000) measures of total schooling for the male and female populations older than 25. We calculated the years of schooling for the groups aged 15-19 and 20-24 by combining Barro and Lee's 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 older than 15 equals the weighted average of schooling for the 15-24 population and schooling for the population older than 25 where the weights are population shares.

As data on capital stocks for the time period we are interested in are meager for most countries, we generate a capital stock series for each country using a perpetual inventory method. We initialize the capital stock series in the first year for the Penn World Tables (version 5.6) provide investment data, setting the capital stock 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 0.07, 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 percent, plus the level of current investment.

Our capital stock series has wider coverage than the Heston and Summers (1994) variable for capital stock per worker, which is only available for 62 countries from 1965 onward. 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 similar. For many countries investment series do not start until 1960, suggesting that our capital stock data for the 1960s 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 1970-90, though we use data from 1960-70 as instruments.

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

4. Estimation and Results

We begin by estimating equation (5) under the assumption that steady-state TFP levels are the same in every country, or in other words $a^*_{it} = a^*_t$. 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 to proxy the average global level of TFP in each period; these appear in levels in the catch-up part of the regression, while the differences between successive time periods measure growth in average TFP over the period.

[insert table 1 about here]

The results in column (1) of table 1 include only physical capital, labor, and schooling as inputs. We find coefficients of close to 0.5 for both capital and labor. We can show that under certain standard assumptions about technology and competition (specifically, that technology displays constant returns to scale and that input markets are perfectly competitive), these coefficients should be equal to the share of each of these inputs in national income. This makes us suspect the results of this estimation, because the respective shares of capital and labor in national income are typically one-third and two-thirds, respectively (see Mankiw 1994, p. 74). However, the sum of these coefficients is close to one, which is what we would expect under constant returns to scale technology. Our estimate of the coefficient on schooling translates into a social rate of return of 17.2 percent[2], which is somewhat higher than the average of 9.1 percent found in microeconomic studies. However, while we find that this estimated rate of return to schooling is significantly different from zero, it is not well determined, and we cannot reject the hypothesis that it is the same as the microeconomic estimate of 9.1 percent. The catch-up coefficient is 0.196, indicating that almost 20 percent of the gap between a

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[2] When an individual stays in school for an extra year, the marginal benefit is given by $\frac{\partial Y_{it}}{\partial S_{it}} = \phi \frac{Y_{it}}{L_{it}}$, where S_{it}, which represents the total years of schooling in the population, is related to the average years of schooling s_{it} in the production function (1) by $s_{it} = \frac{S_{it}}{L_{it}}$. The marginal cost of this decision is that

country's actual and steady-state TFP is closed over a decade, implying an annual rate of convergence of about 2 percent.

Adding experience variables in column (2) has the effect that none of the human capital coefficients is now significant. However, when we calculate the rate of return to schooling we get 12.8 percent, which is statistically different from zero, though once again we cannot reject the hypothesis that the actual rate of return is 9.1 percent. The coefficients on average experience and average experience squared are large in absolute size, though poorly determined. We cannot reject the possibility 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 microeconomic studies.

The reason for the poorly determined coefficients on our experience measures seems to be that in our sample average experience and average of experience squared are 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 is almost completely linear.[3] The wide range of years of work experience we see in microeconomic data allows us to identify the nonlinear relationship between experience and wages, but in macroeconomic data the small

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individual's forgone production $\frac{\partial Y_{it}}{\partial L_{it}} = \beta \frac{Y_{it}}{L_{it}}$. The social rate of return is the ratio of benefits to costs, $\frac{\phi}{\beta} = \frac{.085}{.493} = .172$.

[3] 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, but also that the variance of experience across the work force is similar across countries.

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 are jointly statistically significant, but we cannot reject the hypothesis that the coefficients are equal to those found in microeconomic studies. The coefficient on life expectancy is 0.01, suggesting that increasing life expectancy by one year improves work force productivity and raises output by about 1 percent, though this effect is not well determined and the coefficient is not statistically significant. Note that in column 3 the coefficients on capital and labor take on values that are close to their stylized factor shares of one-third and two-thirds.

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 that the coefficients on the levels and growth rates of inputs are equal.

We do not report estimates of world technology levels, and these are not fully identified. We can estimate the total technology effect for each period (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 without imposing additional restrictions. The problem is that if we see rapid growth in a particular period, we cannot say if it is because the base year TFP level was high and all countries are converging toward this, or because world TFP has grown quickly during the period.[4]

Overall, the picture that emerges from table 1 is that the macroeconomic results are surprisingly close to the results found in microeconomic studies. In every case we find 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 appear to have constant returns to scale, though in some the coefficient on physical capital appears to be closer to half rather than the one-third that seems to be the stylized fact. TFP exhibits large gaps across countries, but these gaps are being closed at the rate of about 2 percent 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 the percentage of land area in the tropics and a measure of governance 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 (5).

Table 2 excludes average experience squared from the estimation. 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 microeconomic data coefficients) is about 1.8 percent, and the expected effect on output (assuming no

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

externalities) is therefore just $(1.8 \times \beta)$ percent implying a coefficient on experience in our regressions of around 0.01.

[insert table 2 about here]

In all three columns of table 2 the coefficient on schooling is small and not statistically significant. However, we cannot reject the possibility that the rate of return to schooling is 0.091 as given by microeconomic 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 raises the productivity of workers and leads to an increase of 4 percent in output. This is only slightly stronger than the effect found in most studies of the contribution of health to economic growth.[5]

[5] Studies of the contribution of health to growth often fit regressions of the form $y_{it} - y_{it-1} = \alpha_0 y_{it-1} + \alpha_1 \ln h_{it} + \alpha_2 x_{it} + \varepsilon_{it}$, where y_{it} is log of per capita output, h_{it} is life expectancy, and x_{it} represents other regressors. When output reaches the steady state, $y_{it} - y_{it-1} = 0$ and simple computation shows that $\frac{\partial y_{it}}{\partial h_{it}} = \frac{-\alpha_1}{\alpha_0 h_{it}}$. This quantity should be directly comparable to our coefficient on life expectancy of 0.04. We can compute this quantity using representative results from Bloom, Canning, Graham, and Sevilla (2000) which have $\alpha_0 = -1.69, \alpha_1 = 2.81, \overline{h}_{it} = 63$ giving us

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. An F-test of the joint significance of the governance and tropics variables in each of the specifications in Table 2 shows these to be significant at the 5% level, allowing us to reject the assumption underlying Table 1, that steady state TFP is constant across countries. The speed of TFP convergence is again around 2 to 2.5 percent a year.

While our results generally agree with those found in microeconomic –studies, our parameter 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, aggregate data exhibit a great deal of multicollinearity; capital intensity, education level, and health status all tend to move together. 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 work experience).

Determining the rates of return to inputs from macroeconomic data with any precision is likely to be difficult. This suggests that so long as the aggregate data do not suggest the presence of large externalities, calibrating macroeconomic models using estimates of private returns from microeconomic studies is useful.

5. Conclusion

$\frac{\partial y_{it}}{\partial h_{it}} = 0.0264$. Thus our present results imply somewhat larger returns to health than previous cross-

Our model accounts for economic growth by the growth of factor inputs, technological innovation, and technological diffusion. Our main result, consistent with our theoretical argument and with the microeconomic evidence, is that health has a positive and statistically significant effect on economic growth. It suggests that a one-year improvement in a population's life expectancy contributes to an increase of 4 percent in output. This is a relatively large effect, indicating that increased expenditures on improving health might be justified purely on the grounds of their impact on labor productivity.

We find no evidence that the macroeconomic effects of education and experience are any greater than those found in microeconomic 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. 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 labor productivity. 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)). Thus 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 multidimensional, showing not only how inputs and

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country studies.

technology affect output, but how the growth rates of inputs and their productivity are themselves determined.

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Table 1. Production Function in Growth Form, Common Long-Run TFP Across Countries
Dependent variable: growth rate of GDP; Nonlinear two stage least squares estimates

Right-hand side variables	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)

d.o.f.: degrees of freedom
Estimated asymptotic standard errors are reported in parentheses below parameter estimates.
* Significant at the 5 percent level.
Note: Estimated on a panel of 104 countries for the growth periods 1970-80 and 1980-90.
Year dummies are included throughout.
Source: Authors' calculations.

Table 2. Production Function in Growth Form, Country-Specific Long-Run TFP
Dependent variable: growth rate of GDP; Nonlinear two stage least squares estimates

Right-hand side variables	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)
Percentage of 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)
Test of joint significance of governance and tropics (chi-square d.o.f. under null)	8.826* (2)	8.130* (2)	12.885* (2)

d.o.f.: degrees of freedom
Estimated asymptotic standard errors are reported in parentheses below parameter estimates.
* Significant at the 5 percent level.
Note: Year dummies are included throughout.
Source: Authors' calculations.