CDDRL
WORKING PAPERS

Health and Economic Growth: Reconciling the Micro and Macro Evidence

David E. Bloom
David Canning

Center on Democracy, Development, and The Rule of Law
Stanford Institute on International Studies

Number 42
February 2005

This working paper was produced as part of CDDRL's ongoing programming on economic and political development in transitional states. Additional working papers appear on CDDRL's website: http://cddrl.stanford.edu.

Center on Democracy, Development,
and The Rule of Law
Stanford Institute of International Studies
Stanford University
Encina Hall
Stanford, CA 94305
Phone: 650-724-7197
Fax: 650-724-2996
http://cddrl.stanford.edu/

About the Center on Democracy, Development and the Rule of Law (CDDRL)

CDDRL was founded by a generous grant from the Bill and Flora Hewlett Foundation in October in 2002 as part of the Stanford Institute for International Studies at Stanford University. The Center supports analytic studies, policy relevant research, training and outreach activities to assist developing countries in the design and implementation of policies to foster growth, democracy, and the rule of law.

About the Authors

David Bloom is a Clarence James Gamble Professor of Economics and Demography, and is Chair of the Department of Population and International Health at Harvard University. His current research interests include labor economics, health, demography, and the environment. Professor Bloom's recent publications include: "How Demographic Change Can Bolster Economic Performance in Developing Countries," *World Economics* (October-December 2003); and "The Effect of Health on Economic Growth: A Production Function Approach," *World Development* (Vol. 32, No. 1, pp 1-13, 2004).

David Canning is Professor of Economics and International Health at Harvard University's Department of Population and International Health. Professor Canning's research focuses on the role of demographic change and health improvements in economic development. His recent publications include: "The Health and Wealth of Africa," with David E. Bloom, *World Economics* (Vol. 5, No. 2, pp 57-81, 2004); and "Geography and Poverty Traps," with David E. Bloom and Jaypee Sevilla, *Journal of Economic Growth* (Vol. 8, pp. 355-378, 2003).

Health and Economic Growth:
Reconciling the Micro and Macro Evidence

February 2005

David E. Bloom and David Canning[1]
Harvard School of Public Health

Abstract

We compare the estimated effects of health in a macroeconomic production function model of economic growth with the effects that are found using calibration based on wage regressions. We allow for gradual adjustment in income level towards the steady state which means that both the level and growth of inputs can affect economic growth. We find that the estimated macroeconomic effects of health are positive, and not significantly different from the microeconomic estimates. We find similar results for education provided we instrument schooling levels with literacy rates to correct for measurement error.

[1] Corresponding author email: dcanning@hsph.harvard.edu

1. Introduction

Health is an important form of human capital. It can enhance workers' productivity by increasing their physical capacities, such as strength and endurance, as well as their mental capacities, such as cognitive functioning and reasoning ability. We expect to see a positive relationship between health and productivity for both unskilled and skilled workers. Evidence of this link is increasing at the microeconomic level (Savedoff and Schultz 2000; Schultz 1999a, 1999b, 2002; Schultz and Tansel 1992; Strauss and Thomas 1998).

A link also exists between health and income at the macroeconomic level. Strong cross-country correlations between measures of aggregate health, such as life expectancy or child mortality, and per capita income are well established (Preston 1975; World Bank 1993). Social scientists commonly regard these correlations as reflective of a causal link running from income to health (see, for example, McKeown 1976; Pritchett and Summers 1996). Higher incomes promote access to many of the goods and services believed to produce health and longevity, such as a nutritious diet, safe water and sanitation, and good health care, but this standard view has been challenged in recent years by the possibility that the income-health correlation is also explained by a causal link running the other way, from health to income.

There are plausible pathways through which health improvements can influence the pace of income growth via their effects on labor market participation, worker productivity, investments in human capital, savings, fertility, and population age structure (Bloom and Canning 2000; Bloom, Canning, and Sevilla 2002a; Bloom, Canning, and Graham 2003; Commission on Macroeconomics and Health 2001; Easterlin 1999; Hamoudi and Sachs 1999). A common empirical approach toward studying the effect of health on economic growth is to focus on data for a cross-section of countries and to regress the rate of growth of income per capita on the initial level of health (typically measured by life expectancy), with controls for the initial level of income and for other factors believed to influence steady-state income levels. These factors might include, for example, policy variables such as openness to trade; measures of institutional quality, educational attainment, and rate of population growth; and geographic characteristics.

Barro and Sala-I-Martin (1995) describe the theoretical framework that underlies the specification of this conditional convergence model. Nearly all studies that have examined economic growth in this way have found evidence of a positive, significant, and sizable influence of life expectancy (or some related health indicator) on the subsequent pace of economic growth (see, for example, Barro 1991, 1996; Barro and Lee 1994; Barro and Sala-I-Martin 1995; Bhargava and others 2001; Bloom, Canning, and Sevilla 2004; Easterly and Levine 1997; Gallup and Sachs 2000; Sachs and Warner 1995, 1997). These studies differ substantially in terms of country samples, time frames, control variables, functional forms, data definitions and configurations, and estimation techniques. Nevertheless, parameter estimates of the effects of life expectancy and age structure on economic growth have been reasonably comparable across studies. While the results of empirical growth equations are generally not completely robust, Levine and Renelt (1992) and Sala-I-Martin (1997a, 1997b) find that out of more than 32,000 regressions involving permutations of over 60 variables, initial life expectancy is a positive and significant predictor of economic growth during 1960–92 in more than 96 percent of the specifications. This makes initial health one of the most robust predictors of subsequent economic growth.

The aim of this paper is to compare the size of the microeconomic estimates of the effect of health on wages with the macroeconomic estimates of the effect of health on worker productivity. Some studies do this by aggregating the microeconomic effects of health to find the implication for aggregate output. For example, Fogel (1994, 1997) argues that a large part of British economic growth during 1780—1980 (about 0.33 percent a year) was due to increases in effective labor inputs that resulted from workers' better nutrition and improved health. Using a similar methodology, Sohn (2000) argues that improved nutrition increased available labor inputs in the Republic of Korea by 1 percent a year or more during 1962–95. We, however, concentrate on the work of Weil (2001) and Shastry and Weil (2003), who model output using an aggregate production function and calibrate the parameters of the production function using microeconomic evidence. Using microeconomic evidence on factor shares and the effect of human capital on wages to calibrate production function models of aggregate output has become quite common (see, for example, Klenow and Rodriguez-Clare 1997; Prescott 1998; Young 1994, 1995). Weil (2001) and Shastry and Weil (2003) add health to the production function and calibrate the effect of adult survival rates on aggregate output.

As a country's health improves, as measured, for example, by average adult height or the prevalence of anemia, we would expect to see an improvement in labor productivity and output per worker. However, directly using the relationship between height or anemia and productivity at the microeconomic level to predict economic performance at the macroeconomic level is difficult, because we do not have consistent measures of population heights and anemia across countries and across time. Weil (2001) tries to overcome this problem by calculating a relationship between adult height in a population and the population’s adult survival rate (the proportion of 15-year-olds who would live to age 60 at current mortality rates). Weil shows that adult heights and survival rates move together, and postulates a set of stable relationships between a population’s health, height, and adult survival rate. In this way he calibrates a relationship between health as measured by adult survival rates and labor productivity across countries.

The result of this calibration exercise is that a one percentage point increase in adult survival rates translates into a 1.68 percent increase in labor productivity. This means that a worker in good health in a low-mortality country will be about 70 percent more productive than a worker suffering from ill health in a high-mortality environment. This is a large effect and implies that health differentials account for about 17 percent of the variation in output per worker across countries. This is roughly the same magnitude as the differences accounted for by physical capital (18 percent) and education (21 percent). Weil ascribes the source of the remaining 43 percent of the variation to differences in total factor productivity (TFP) across countries.

This calibration exercise suggests that health is a vitally important form of human capital and deserves the same level of attention in the development process as is currently paid to the accumulation of physical capital and education. In particular, public health measures in developing countries, such as vaccination and antibiotic distribution programs, can lead to large improvements in health outcomes at relatively low costs (Commission on Macroeconomics and Health 2001; World Bank 1993). If health is an important form of human capital and as such is a productive asset, this adds a strong argument for extra investment in health over and above the direct welfare benefits that good health brings.

The validity of this argument depends on the accuracy of the calibration result. An alternative approach is to estimate the production function directly (see, for example, Caselli, Esquivel, and Lefort 1996; Duffy and Papageorgiou 2000; Mankiw, Romer, and Weil 1992). The advantage of estimation is that it can potentially capture the effects of health and education on productivity, which calibration based on wage equations may miss (Mankiw 1997). While better health may lead to improved wages, these wages may differ from the marginal product of labor. For example, wages may reflect rents accruing to positions in a social hierarchy obtained by being tall and having good schooling and may bear little relationship to productivity. Wages may also capture only the private returns to health and miss any beneficial externalities associated with good health. Having evidence that the effect of health on worker productivity can been seen in aggregate output would complement the evidence that health affects wages and strengthen the argument for investments in health.

We therefore estimate a production function model of economic growth, keeping our specification as close as possible to that of Weil (2001) to permit direct comparison between our estimates and his calibrated parameters. Estimating an aggregate production function using cross-country data is difficult, because reverse causality, omitted variable bias, and measurement error in the explanatory variables may lead to inconsistencies in parameter estimates. In what follows, we try to take all three of these issues into account.

In particular, we try to control for different countries' varying levels of TFP and rates of technological progress. Failure to control for these differences tends to lead to overestimation of the impact of input on output: countries with high TFP will have high output, and hence will have the resources to invest in health and education, thereby creating a correlation caused by reverse causality. We model differences in TFP using the methods set out in De La Fuente and Domenech (2001) and Bloom, Canning, and Sevilla (2004) allowing for different steady-state levels of TFP across countries and diffusion of technology over time.

We find that health, in the form of adult survival rates, makes a positive and statistically significant contribution to aggregate output. In addition, while we estimate a somewhat larger parameter value, we cannot reject the hypothesis that a one percentage point increase in adult survival rate raises worker productivity by 1.68 percent. Our results are therefore completely consistent with the calibration approach Weil (2001) uses. Note that since we include capital and education in our regressions our estimate is a measure of the direct productivity benefits of health and excludes any effect that operates through a longer expected life span on investments in capital accumulation or education.

We find that the effect of schooling on productivity is small and not statistically significant. De La Fuente and Domenech (2001) find a similar result and suggest that this is due to measurement error in the schooling data, and once they restrict the sample to OECD countries and construct an improved dataset of the level of schooling, they do find a significant effect. We keep our large cross-country sample, but overcome the measurement problem by instrumenting years of schooling with literacy rates. Once we do this, our estimates of the effect of schooling become larger and are consistent with calibrated values, implying that we find no conflict between calibration and estimation of the effect of human capital in the aggregate production function.

2. The Aggregate Production Function

We follow Weil (2001) and model the aggregate production as

$$Y = AK^{\alpha}(Lv)^{\beta} \qquad (1)$$

where Y is total gross domestic product (GDP), A represents TFP, K is the physical capital stock, and L is the labor force. We take v to be the level of human capital in per capita terms and define $V = Lv$ as effective labor input. The wage w earned by a unit of composite labor V is its marginal product as follows:

$$w = \frac{dY}{dV} = \beta\frac{Y}{V} \qquad (2)$$

A worker with v_j units of human capital will therefore earn a wage of

$$w_j = wv_j \qquad (3)$$

Let us model the human capital of worker j by the expression

$$v_j = \mathrm{e}^{\phi_s s_j + \phi_h h_j} \qquad (4)$$

where s_j represents years of schooling and h_j represents health. This normalizes the effective labor input of a worker with no education and a zero on our health measure to be one, while workers with higher levels of education and health may be equivalent, in productivity terms, to a larger number of such baseline workers This has the advantage that we can now derive the following equation for wages at the individual level:

$$\log w_j = \log(w) + \log(v_j) = \log(w) + \phi_s s_j + \phi_h h_j . \qquad (5)$$

This is consistent with the Mincer wage equation in that it links years of schooling to log wages. Note that the intercept of the wage equation log(w) is the log wage of a worker with no education and zero health on our measure, and that this will vary across countries. The aggregate production function (equation 1) with our measure of human capital (equation 4) is therefore consistent with the form of the wage equation found at the microeconomic level. Note that we exclude worker experience from our measure of human capital. Worker experience and experience squared vary a great deal across individuals but are highly correlated and vary little across countries; higher average ages in countries with longer life expectancies tend to be offset by high levels of schooling and later entry to the workforce. This makes estimating the effect of experience in macroeconomic models difficult (see Bloom, Canning and Sevilla (2004) for an example).

One problem remains with this approach. It implies that the total level of human capital in the economy is

$$V = \sum_j v_j = \sum_j e^{\phi_s s_j + \phi_h h_j} \qquad (6)$$

This means we should raise years of schooling and our health measure for individuals to the exponential power before summing to obtain total human capital. National statistics tend to give simple arithmetic averages. However, if we assume that the distribution of human capital, and hence of wages, is lognormal, the log of the average wage will be the log of the median wage plus half the variance of wages. But for a lognormal distribution, the log of the median wage equals the average of log wages, because log wages have a symmetric distribution. Hence

$$\log V = \log(\sum_j v_j / L) = (\sum_j \log v_j) / L + \sigma^2 / 2 = \sum_j (\phi_s s_j + \phi_h h_j) / L + \sigma^2 / 2 \qquad (7)$$

and so

$$\log V = \phi_s s + \phi_h h + \sigma^2 / 2 \qquad (8)$$

where σ is the standard deviation of log wages and *s* and *h* represent the average levels of schooling and health in the workforce. The intuition for this result is that *s* measures the average years of schooling; however, a year of schooling raises a worker's productivity and wages by $100\phi_s$ percent. The absolute size of this effect is larger for highly educated, high-wage earners than for poorly educated, low-wage workers. Of course, an extra year of education for a highly educated worker also represents a greater investment, because it is more costly to produce in that the worker must forego a higher wage while undertaking the extra schooling.

In what follows, we ignore the effect of the distribution of human capital and wages on aggregate productivity. While cross-country measures of income inequality do exist (see, for instance, Deininger and Squire 1996), they may not be reliable (Atkinson and Brandolini 2001).

Taking logs, our aggregate production function is

$$\log Y = a + \alpha \log K + \beta(\log L + \phi_s s + \phi_h h) . \qquad (9)$$

The use of rates of return to calibrate the coefficient on education suggests a parameter value of around 0.091 based on an average rate of return of 9.1 percent (taken from the cross-section of studies reported in Bils and Klenow 2000, which are based on the work of Psacharopoulos 1994). Investigators generally agree on values of around one-third for α, the coefficient on capital, and around two-thirds for β, the coefficient on labor, based on the shares of profits and wages in national income (see, for example, Hall and Jones 1999).

Heckman and Klenow (1997) and Krueger and Lindahl (2001) take a similar approach deriving a macroeconomic equation showing the effects of aggregate schooling based on aggregating up the Mincer wage equation. The major difference is that in their formulation the effect of the education level on output is simply ϕ_s whereas in our approach the effect of schooling is $\beta\phi_s$. This difference arises because they take the cross country differences and changes in the intercepts in equation (5) to be random and assign them to the error term in the regression. With our production function increases in schooling increase the aggregate level of human capital, and labor equivalent inputs in the economy, and depress the wage paid per equivalent worker.

3. Total Factor Productivity and Economic Growth

Using the aggregate production function (equation 9), we can express output in country *i* at time *t* as

$$y_{it} = a_{it} + \alpha k_{it} + \beta(l_{it} + \phi_s s_{it} + \phi_h h_{it}) , \qquad (10)$$

where y_{it}, k_{it} and l_{it} are the logs of Y_{it}, K_{it} and L_{it}, respectively. Equation (10) is an identity, but in practice a_{it}, the level of TFP in country *i* at time *t*, is not observed directly. Several approaches are available for modeling TFP across countries and across time. We follow Bloom, Canning, and Sevilla (2002b) and model TFP as following a diffusion process across countries, but with the possibility of long-run differences in TFP even after diffusion is complete. Formally let

$$\Delta a_{it} = \lambda(a_{it}^{*} - a_{i,t-1}) + \varepsilon_{it} \qquad (11)$$

where ε_{it} is a random shock. Each country has a ceiling level of TFP given by a_{it}^{*}. The country's TFP adjusts toward this ceiling at rate λ. We assume that the ceiling level of TFP for a country depends both on country characteristics and on the worldwide technology frontier. We can model this by

$$a_{it}^{*} = \delta x_{it} + a_t \qquad (12)$$

where x_{it} represents a set of country-specific variables that affect TFP and a_t is a time dummy representing the current level of worldwide TFP. Investigators have suggested several variables that may affect long-run TFP. For example, Hall and Jones (1999) argue that institutions and "social infrastructure" can affect productivity, while Gallup, Sachs, and Mellinger (1999) emphasize the role of geography. Our empirical work experiments with a range of likely variables.

Because technology gaps are not directly observed, one strand of the literature follows Baumol (1986) and proxies $a_{i,t-1}$ in equation (11) with lagged income per worker (see, for example, Fagerberg 1994, and more recently Dowrick and Rogers 2002). However, we measure the lagged technology level directly by using the fact that by rearranging equation (10), the lagged level of total factor productivity is

$$a_{i,t-1} = \alpha k_{i,t-1} + \beta(l_{i,t-1} + \phi_s s_{i,t-1} + \phi_h h_{i,t-1}) - y_{i,t-1} \qquad (13)$$

Differencing the production function (equation 10) gives us

$$\Delta y_{it} = \Delta a_{it} + \alpha \Delta k_{it} + \beta(\Delta l_{it} + \phi_s \Delta s_{it} + \phi_h \Delta h_{it}) \qquad (14)$$

so that growth in output depends on the growth of inputs plus the growth of TFP. Substituting for Δa_{it} using equations (11) and (12) gives us the following growth equation:

$$\Delta y_{it} = \alpha \Delta k_{it} + \beta(\Delta l_{it} + \phi_s \Delta s_{it} + \phi_h \Delta h_{it})$$
$$+\lambda(a_t + \delta x_{it} + \alpha k_{i,t-1} + \beta(l_{i,t-1} + \phi_s s_{i,t-1} + \phi_h h_{i,t-1}) - y_{i,t-1}) + \varepsilon_{it} \qquad (15)$$

De La Fuente and Domenech (2001) and Bloom, Canning, and Sevilla (2002b) use this approach to model TFP diffusion in cross-country production function studies, and it is formally equivalent to the autoregressive model of TFP Griliches and Mairesse (1998) and Blundell and Bond (2000) use in their studies of the production function using firm-level data.

Equation (15) shows that growth in output can be decomposed into three components. The first is the growth of the capital, labor, schooling, and health inputs. The second is a catch-up term, as some of the country's TFP gap, $a_{i,t-1}$, is closed, and the country converges at the rate λ to its ceiling level of TFP. The third is an idiosyncratic shock to the country's TFP, ε_{it}.[2]

In the special case that $\lambda = 0$ (no technological diffusion), the lagged level terms in equation (15) disappear. Thus our approach encompasses the estimation of the production function in first differences as advocated by Pritchett (1997) and Krueger and Lindahl (2001), and we can test if this restriction holds. Taking first differences nets out any fixed effects on TFP. Therefore testing $\lambda = 0$ tests the null of a fixed effects model, with persistent differentials in TFP, against the alternative that TFP differentials narrow over time because of technological diffusion. Our model also encompasses the special case where there is technological diffusion, but the steady-state level of TFP is the same in every country. We can test this by examining whether the country-specific variables x_{it} have zero coefficients.

Equation (15) is essentially a model of conditional convergence. The speed of convergence, λ, is the rate at which TFP gaps are converging. This is in sharp contrast with models such as those of Mankiw, Romer, and Weil (1992) and Islam (1995), which take TFP differentials across countries to be fixed. The speed of convergence in these models depends on the time capital stocks take to reach their steady-state levels given fixed investment rates. By including the growth rates of factor inputs directly in equation (15), we can identify the catch-up term—the effect of the gap between actual output and steady-state output given current input levels—as the impact of a TFP gap.

In estimating equation (15) we face the possibility that the contemporaneous growth rates of factor inputs are endogenous and responsive to the current TFP shock ε_{it}. We overcome this problem by instrumenting these current input growth rates with lagged input growth rates.[3] We assume that these lagged input growth rates and the lagged levels of inputs are uncorrelated with ε_{it}, the current shock to TFP. This is quite compatible with lagged TFP levels and expected TFP growth (the catch-up term in equation 15) affecting previous input decisions (for example,

[2] We could allow the shock to growth during each period to have a common component across countries, for example, worldwide oil or interest rate shocks. This creates a time dummy. This time dummy is, however, co-linear with the worldwide productivity ceiling a_t and will not affect any of our results.

[3] Simply using the lagged level of the input as an instrument for both itself and for its growth rate is possible, because we are estimating only one parameter for each input. However, having a separate instrument for the growth of each input increases the precision of our estimate and also allows us to estimate the growth and level effects separately and to test the common factor restriction.

Bils and Klenow 2000 suggest that schooling decisions depend on expected economic growth). The argument that the lagged input levels are uncorrelated with future shocks to TFP is the real rationale for estimating equation (15) rather than the level relationship in equation (10). For this argument to be valid, shocks to TFP (the error term in our regressions) must not be predicable.

If the shocks to TFP, ε_{it}, are correlated over time, lagged endogenous variables that are correlated with $\varepsilon_{i,t-1}$ or $\varepsilon_{i,t-2}$ will become correlated with ε_{it} through the autocorrelation structure and will no longer be valid instruments. We use an over-identifying restriction test to check for the validity of our instruments. Given the importance of instrument validity, we also test for autocorrelation of the shocks to TFP directly. Residual-based tests of autocorrelation in models such as ours are complicated by the fact that under the alternative of autocorrelation, the instruments are no longer valid (see, for example, Cumby and Huizinga 1992, who derive residual-based tests for linear models that use lagged variables as instruments). We therefore follow Dezhbakhsh and Thursby (1994) and test for first-order serial correlation by transforming the model. Under the alternative of first-order serial correlation in the shocks to TFP (so that TFP itself has a second-order autocorrelation structure), we have $\varepsilon_{it} = \rho\varepsilon_{i,t-1} + u_{it}$, where u_{it} is now assumed to be an i.i.d. process. We can now transform equation (15) to give

$$\begin{aligned}
\Delta y_{it} &= \alpha\Delta k_{it} + \beta(\Delta l_{it} + \phi_s \Delta s_{it} + \phi_h \Delta h_{it}) \\
&+\lambda(a_t + \delta x_i + \alpha k_{i,t-1} + \beta(l_{i,t-1} + \phi_s s_{i,t-1} + \phi_h h_{i,t-1}) - y_{i,t-1}) \\
&+\rho[\Delta y_{i,t-1} + \alpha\Delta k_{i,t-1} + \beta(\Delta l_{i,t-1} + \phi_s \Delta s_{i,t-1} + \phi_h \Delta h_{i,t-1}) \\
&+\lambda(a_{t-1} + \delta x_{i,t-1} + \alpha k_{i,t-2} + \beta(l_{i,t-2} + \phi_s s_{i,t-1} + \phi_h h_{i,t-2}) - y_{i,t-2})] + u_{it} \qquad (16)
\end{aligned}$$

Again, current growth rates of inputs in the first line of equation (16) are likely to be correlated with u_{it} and are instrumented. Note that while all our instruments appear in equation (16), because of the additional lag terms, only one extra parameter, ρ, has to be estimated, and the model remains identified. Estimating equation (16) allows us to test for the presence of autocorrelation using a simple t-test for the significance of ρ.

In addition, our model imposes some “common factor” restrictions: the coefficient on each lagged input level in the catch-up term should be the same as on its current growth rate. Failure to satisfy these common factor restrictions would be evidence of misspecification.

We model country-specific effects on long–run, steady-state TFP using a number of observable country characteristics. Following Griliches and Mairesse (1998) and Blundell and Bond (2000) and estimating a fixed effects model to allow for unobserved factors that may have persistent effects on TFP would be desirable. However, experimentation with dynamic panel GMM methods produced estimates with large standard errors in which no variables were statistically significant. To remove the fixed effect from equation (15) we have to difference the relationship again, leading to an empirical specification in which the level terms disappear. In addition, over the five-year intervals we use we take the view that all the inputs are potentially correlated with contemporaneous productivity shocks. This means that all our regressors must be instrumented by lagged values, as opposed to the firm-level studies, in which current inputs are treated as exogenous. Both these factors imply a loss of precision in the estimates and make inferences based on a fixed effects approach difficult.

4. Data

We construct a panel of countries observed every five years from 1960 through 1995. Output data (GDP) are obtained from the Penn World Tables version 6.0 (see Heston and Summers 1994 for a description).[4] We obtain total output by multiplying real per capita GDP measured in 1985 international purchasing power parity dollars (chain index) by national population.

Data on the economically active population are from the International Labour Office (1997). This is an imperfect measure, because it fails to account for variations across countries in unemployment rates and hours worked. In addition, the data only include figures for 1960, 1970, 1980, 1990, and 1995. For 1965, 1975, and 1985 we construct our own estimates of the economically active population. The International Labour Office data give activity rates by sex by five-year age cohort. We interpolate these activity rates and use the data on population by sex and five-year age cohort from the United Nations (1998) to generate our estimates of the economically active population for these years.

Average schooling is measured as a weighted average of the total years of schooling of the male and female populations age 25 and up taken from Barro and Lee (2000). The weights in this construction are the male and female shares of the economically active population. We also experiment with a number of other options, such as using the weighted averages of the population age 15 and older, or simply using the population weighted (rather than the economically active population weighted) averages of the male and female schooling levels.

Life expectancy and infant mortality data are from the United Nations (1998). In our analysis we use adult survival rates as our measure of population health. Conceptually, this measure may be more closely related to adult health and worker productivity than to life expectancy, a measure that is highly sensitive to infant mortality rates. However, adult survival rates act only as a proxy for the health of the workforce, because they measure mortality rates rather than morbidity. Our main reason for using adult survival rates is that it allows us to compare our results directly with those of Weil (2001) and Shastry and Weil (2003). Raw data on adult survival rates are taken from the World Bank (2001). As with labor force data, adult survival rates are not available for 1965, 1975, and 1985. We therefore estimate a relationship, explaining adult survival rates using life expectancy, life expectancy squared, infant mortality, infant mortality squared, and infant mortality times life expectancy. We carry this out separately for males and females using the appropriate life expectancy variable. This estimated relationship is quite good (R^2 of 0.96 for males and 0.97 for females), which is not surprising given that the raw data on adult survival rates are often constructed using life tables based on such measures as infant mortality (see, for example, Bos and others 1998; Pritchett and Summers 1996). We then calculate the average adult survival rate of the economically active population as the weighted average of the estimated sex-specific adult survival rates (with shares of the economically active population used as weights).

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 investment data are available in the Penn World Tables (version 6.0), 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 0.07, our assumed depreciation rate. This is the capital stock we would expect in the initial year if the

[4] Penn World Tables Version 6 downloaded from http://pwt.econ.upenn.edu/.

investment/GDP ratio we use is representative of previous rates. Each succeeding period's capital is given by current capital, minus depreciation, plus the level of current investment.

Our capital stock series has somewhat wider coverage than the Heston-Summers variable for capital stock per worker, *kapw*, which is only available for 62 countries from 1965 onward. Where the series overlap, the correlation coefficient between the log levels of the two is 0.965, indicating that the two series are very similar. This perpetual inventory method of measuring capital may, however, introduce substantial measurement error, particularly if investment flows do not accurately measure the addition to public capital because of waste and corruption (Pritchett 2000).

We include some country-specific variables that may affect the long-run level of TFP. These are a measure of ethno-linguistic fractionalization from Easterly and Levine (1997), the Sachs and Warner (1995) measure of openness to trade (which also depends to some extent on a country's market institutions), and an indicator for the quality of institutions from Knack and Keefer (1995). We also use the percentage of land area in the tropics and a dummy for being landlocked from Gallup, Sachs, and Mellinger (1999) to control for geographical factors that may affect productivity and trading opportunities.

5. Estimation Results

We estimate the parameters of equation (15) on a panel of countries using quinquennial data for 1965–95. We estimate the parameters by nonlinear least squares, instrumenting the current growth rates of the factor inputs using lagged growth rates of the inputs, plus lagged output growth. We experimented with five variables that might affect the ceiling level of TFP: openness to trade, percentage of land area in the tropics, a measure of institutional quality, ethno-linguistic fractionalization of the population, and a country dummy for being landlocked. Only the first two, openness and percentage of land area in the topics, were ever statistically significant at the 5 percent level. The others were therefore dropped from the regressions, though they remain in our instrument list.

Results using ordinary least squares, treating the growth of inputs as exogenous, and results omitting our proxies for TFP are not reported. We expect positive feedback from high levels of TFP growth (the error term in the regression) to output and incomes to lead to an upward bias in our estimates of the coefficients on accumulated factor inputs. This is exactly what occurs in such regressions, with the coefficient on physical capital frequently being found to lie between 0.6 and 0.7.

Column (1) of table 1 gives estimates of a simple form of the production function including average years of schooling as our only measure of human capital. The results suggest that capital and labor both contribute significantly to aggregate output and that technological diffusion occurs, with about 12 percent of the technology gap being closed in each five-year period. Long-run differences in ceiling levels of TFP are apparent, with countries in the tropics having lower productivity and open economies having higher productivity.

[insert table 1 about here]

Beneath the parameter estimates we report the results of a number of statistical tests. In each case (except for the autocorrelation test discussed earlier) we use the Gallant and Jorgenson (1979) quasi-likelihood ratio test, which is appropriate, because we are estimating a nonlinear model using instrumental variables.

We begin with the tests on the parameter estimates. The estimates in column (1) are consistent with constant returns to scale, that is, we test that the capital and labor coefficients sum to 1. The coefficient on schooling is small and not statistically different from zero; however, we also cannot reject that it is equal to 0.091, the calibrated value given in table 2. Experimenting with other measures of schooling from Barro and Lee (2000) produced very similar results.

[insert table 2 about here]

We also report three specification tests in column (1) of table 1. We begin by testing the common factor restrictions in equation (15), the fact that in the model, the coefficients on the input growth terms are the same as those on the input level terms inside the catch-up expression. While we pass this test, the model fails both the over-identifying restrictions test on the validity of the instruments and the test for autocorrelation. These failures imply that the specification in column (1) is unlikely to be valid.

In column (2) of table 1 we add the adult survival rate as an explanatory variable. We estimate that a one percentage point increase in adult survival rates increases labor productivity by 3 percent. However, while this positive effect is statistically significant at the 1 percent level, we cannot reject the hypothesis that the estimated schooling and health parameters are the same as the calibrated parameters given in table 2. In addition, in column (2) of table 1 the specification tests are satisfactory, so we cannot reject the validity of the instruments or the common factor restriction implied by our specification.

One potential issue is that in the first three columns of table 1 we assume that the coefficient on the adult survival rate is the same in every country, but Bhargava and others (2001) suggest that while the effect of health is large in poorer countries, it falls with income level. To allow for the possibility that the coefficient on the adult survival rate varies with the level of development, we add an adult survival rate squared term in column (4) of table 1.[5] Adding an interactive term with income level is hard to justify in our production function framework (and involves having a current endogenous variable on the right-hand-side of equation 5), while the squared term in the adult survival rate allows for the possibility of diminishing returns to health as the level of development (proxied by the adult survival rate itself) rises. However, while the specification seems satisfactory, the squared term is not statistically significant, and we find no evidence that the health effect varies with the level of development.[6]

6. Conclusion

A great deal of the literature on economic growth has been devoted to studying the impact of education on aggregate economic performance and comparing the results with the rate of return to education identified by the Mincer (1974) log wage equation. We believe that ours is the first study to compare the estimates of the macroeconomic effect of health on output with the microeconomic estimates of the effect of health on wages now available.

We estimate that a one percentage point increase in adult survival rates increases labor productivity by about 2.8 percent, with a 95 percent confidence interval of 1.2 to 4.3 percent.

[5] In column (4) of table 1, the lagged level of adult survival rate squared instruments itself while we instrument its growth with lagged growth in the adult survival rate squared.
[6] Splitting the sample by income level in 1965 we find a similar result with no evidence of a higher coefficient on health in poorer countries.

Our result is therefore somewhat higher than, but consistent with, the calibrated value of around 1.7 percent. This supports Weil's (2001) conclusion, based on calibration, that health plays a large role in explaining cross-country differences in the level of income per worker, a role roughly as important as education.

Indeed, our results would imply a larger role for health than for education. However, while we estimate a small, or even zero, effect for education, we find that this estimate has a large standard error and wide confidence interval. This confidence interval is wide enough to include the 9.1 percent increase in wages and labor productivity associated with an extra year of schooling. So long as macroeconomic estimates do not reject the hypothesis that the productivity effects calibrated on the basis of wage regression are correct, we have no evidence of substantial externalities, allowing us to use calibration based on microeconomic data as a reasonable guide to the magnitude of effects.

References

The word "processed" describes informally reproduced works that may not be commonly available in libraries.

Atkinson, A. B., and A. Brandolini. 2001. "Promise and Pitfalls in the Use of 'Secondary' Data Sets: Income Inequality in OECD Countries as a Case Study." *Journal of Economic Literature* 39(3): 771–99.

Barro, R. 1991. "Economic Growth in a Cross-Section of Countries." *Quarterly Journal of Economics* 106(2): 407–43.

_____. 1996. "Health and Economic Growth." Harvard University, Cambridge, MA. Processed.

Barro, R,. and J. Lee. 1994. "Sources of Economic Growth." *Carnegie-Rochester Conference Series on Public Policy* 40: 1–46.

_____. 2000. "International Data on Educational Attainment: Updates and Implications." Working Paper no. 42. Harvard University Center for International Development, Cambridge, MA.

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

Baumol, W. 1986. "Productivity Growth, Convergence, and Welfare: What the Long-Run Data Show." *American Economic Review* 76(5): 1072–85.

Bhargava, A., D. Jamison, L. Lau, and C. Murray. 2001. "Modeling the Effects of Health on Economic Growth." *Journal of Health Economics* 20(3): 423–40.

Bils, M., and P. Klenow. 2000. "Does Schooling Cause Growth?" *American Economic Review* 90(5): 1160–83.

Bloom, D. E., and D. Canning. 2000. “The Health and Wealth of Nations.” *Science* 287(5456): 1207–08.

Bloom, D. E., D. Canning, and B. Graham. 2003. “Longevity and Life Cycle Savings.” *Scandinavian Journal of Economics* 105(3): 319–38.

Bloom, D. E., D. Canning, and J. Sevilla. 2002a. *The Demographic Dividend: A New Perspective on the Economic Consequences of Population Change*, Santa Monica, Calif.: RAND, MR-1274.

Bloom, D. E., D. Canning, and J. Sevilla. 2002b. “Technological Diffusion, Conditional Convergence, and Economic Growth.” Working Paper no. 8713. National Bureau of Economic Research, Cambridge, MA.

Bloom, D.E., D. Canning, and J. Sevilla. 2004. “The Effect of Health on Economic Growth: A Production Function Approach.” *World Development* 32(1): 1–13.

Blundell, R., and S. Bond. 2000. “GMM Estimation with Persistent Panel Data: An Application to Production Functions.” Working Paper no. 99/4. Institute for Fiscal Studies, London, United Kingdom.

Bos, E., and others. 1998. “Basic Demographic, Health, and Health Systems Data.” Technical Report. Washington, D.C.: World Bank.

Caselli, F., G. Esquivel, and F. Lefort. 1996. “Reopening the Convergence Debate: A New Look at Cross-Country Growth Empirics.” *Journal of Economic Growth* 1(3): 363–89.

Commission on Macroeconomics and Health. 2001. *Macroeconomics and Health: Investing in Health for Economic Development*. Geneva: World Health Organization.

Cumby, R. E., and J. Huizinga. 1992. “Testing the Autocorrelation Structure of Disturbances in Ordinary Least Squares and Instrumental Variable Regressions.” *Econometrica* 60(1): 185–96.

Deininger, K., and L. Squire. 1996. “A New Data Set Measuring Income Inequality.” *World Bank Economic Review* 10(3): 565–91.

De la Fuente, A., and R. Domenech. 2001. “Schooling Data, Technological Diffusion, and the Neoclassical Model.” *American Economic Review Papers and Proceedings* 91(2): 323–27.

Dezhbakhsh, H., and J. G. Thursby. 1994. “Testing for Autocorrelation in the Presence of Lagged Dependent Variables: A Specification Error Approach.” *Journal of Econometrics* 60(1—2): 251–71.

Dowrick, S., and M. Rogers. 2002. “Classical and Technological Convergence: Beyond the Solow-Swan Model.” *Oxford Economic Papers* 54(3): 369–85.

Duffy, J., and C. Papageorgiou. 2000. “A Cross-Country Empirical Investigation of the Aggregate Production Function Specification.” *Journal of Economic Growth* 5(1): 87–120.

Easterlin, R. 1999. “How Beneficent Is the Market? A Look at the Modern History of Mortality.” *European Review of Economic History* 3(3): 257–94.

Easterly, W., and R. Levine. 1997. “Africa's Growth Tragedy: Policies and Ethnic Divisions.” *Quarterly Journal of Economics* 112(4): 1203–50.

Fagerberg, J. 1994. “Technology and International Differences in Growth Rates.” *Journal of Economic Literature* 32(3): 1147–75.

Fogel, R. W. 1994. “Economic Growth, Population Theory, and Physiology: The Bearing of Long-Term Processes on the Making of Economic Policy.” *American Economic Review* 83(3): 369–95.

Fogel, R. W. 1997. “New Findings on Secular Trends in Nutrition and Mortality: Some Implications for Population Theory.” In M. Rosenzweig and O. Stark, eds., *Handbook of Population and Family Economics*, vol. 1A. New York: Elsevier.

Gallant, A. R., and D. W. Jorgenson. 1979. “Statistical Inference for a System of Simultaneous, Nonlinear, Implicit Equations in the Context of Instrumental Variables Estimation.” *Journal of Econometrics* 11(2-3): 275–302.

Gallup, J., and J. Sachs. 2000. “The Economic Burden of Malaria.” Working Paper no. 52. Harvard University, Center for International Development, Cambridge, MA.

Gallup, J. L., J. D. Sachs, and A. D. Mellinger. 1999. “Geography and Economic Development.” *International Regional Science Review* 22(2): 179–232.

Griliches, Z., and J. Mairesse. 1998. “Production Functions: The Search for Identification.” In S. Strom, ed., *Econometrics and Economic Theory in the 20th Century*. Cambridge, U.K.: Cambridge University Press.

Hall, R. E., and C. I. Jones. 1999. “Why Do Some Countries Produce So Much More Output Per Worker Than Others? *Quarterly Journal of Economics* 114(1): 83–116.

Hamoudi, A., and J. Sachs. 1999. “Economic Consequences of Health Status: A Review of the Evidence.” Working Paper no. 30. Harvard Center for International Development, Cambridge, MA.

Hastings, N. A., and J. B. Peacock. 1975. *Statistical Distributions: A Handbook for Students and Practitioners.* Hoboken, NJ: John Wiley and Sons.

Heckman, J. J., and P. J. Klenow. 1997. *Human Capital Policy*. Chicago, IL: University of Chicago Press.

Heston, A., and R. Summers. 1994. *Penn World Tables version 5.6.* Revision of Heston, A., and R. Summers. 1991. "The Penn World Table (Mark 5): An Expanded Set of International Comparisons, 1950-1988." *Quarterly Journal of Economics* 106: 327-68.

International Labour Office. 1997. *Economically Active Population, 1950–2010,* 4th ed. Geneva: International Labor Office, Bureau of Statistics.

Islam, N. 1995. “Growth Empirics: A Panel Data Approach.” *Quarterly Journal of Economics* 110(4): 1127–70.

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

Knack, S., and P. Keefer, 1995. “Institutions and Economic Performance: Cross-Country Tests Using Alternative Institutional Measures.” *Economics and Politics* 7(3): 207–27.

Krueger, A., and M. Lindahl. 2001. “Education for Growth: Why and for Whom?” *Journal of Economic Literature* 39(4): 1101–36.

Levine, R., and D. Renelt. 1992. “A Sensitivity Analysis of Cross-Country Growth Regressions.” *American Economic Review* 82(4): 942–63.

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

Mankiw, N. G., D. Romer, and D. Weil. 1992. A Contribution to the Empirics of Economic Growth. *Quarterly Journal of Economics* 107(2): 407–37.

McKeown, T. 1976. *The Modern Rise of Population.* London: Edward Arnold.

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

Prescott, E. C. 1998. “Needed: A Theory of Total Factor Productivity.” *International Economic Review* 39(3): 525–51.

Preston S. 1975. “The Changing Relation Between Mortality and the Level of Economic Development.” *Population Studies* 29(2): 231–48.

Pritchett, L. 1997. “Where Has All the Education Gone?” Policy Research Paper no. 1581. World Bank, Washington, D.C.

Pritchett, L. 2000. “The Tyranny of Concepts: CUDIE (Cumulated, Depreciated, Investment Effort) Is Not Capital.” *Journal of Economic Growth* 5(4): 361–84.

Pritchett, L,. and L. Summers. 1996. “Wealthier Is Healthier.” *Journal of Human Resources* 31(4): 844–68.

Psacharopoulos, G. 1994. “Returns to Investment in Education: A Global Update.” *World Development*. 22(9): 1325–43.

Sachs, J., and A. Warner. 1995. “Economic Reform and the Process of Global Integration.” *Brookings Papers on Economic Activity* 1: 1–118.

Sachs, J., and A. Warner. 1997. “Sources of Slow Growth in African Economies.” *Journal of African Economics* 6(3): 335—76.

Sala-I-Martin, X. 1997a. “I Just Ran Four Million Regressions.” Working Paper no. 6252. National Bureau of Economic Research, Cambridge, MA.

Sala-I-Martin, X. 1997b. “I Just Ran Two Million Regressions.” *American Economic Review Papers and Proceedings* 87(2): 178–83.

Savedoff, W. D., and T. P. Schultz. 2000. *Wealth from Health*. Washington, D.C.: Inter-American Development Bank.

Schultz, P. 1999a. “Health and Schooling Investments in Africa.” *Journal of Economic Perspectives* 13(3): 67–88.

Schultz, P.. 1999b. “Productive Benefits of Improving Health: Evidence from Low Income Countries.” Yale University, Hartford, CN. Processed.

Schultz, T.P. 2002. “Wage Gains Associated with Height as a Form of Human Capital.” *American Economic Review Papers and Proceedings* 92(2): 349–53.

Schultz, T. P., and A. Tansel. 1992. “Measurement of Returns to Adult Health: Morbidity Effects on Wage Rates in Côte d'Ivoire and Ghana.” Discussion Paper No. 663. Yale University, Economic Growth Center, New Haven, CT.

Shastry, G. K., and D. N. Weil. 2003. “How Much of Cross-Country Income Variation is Explained by Health?” *Journal of the European Economic Association,*1(2-3): 387–96.

Sohn, B. 2000. “How Much Has Health Improvement Contributed to the Korean Economic Growth?” Brown University, Providence, RI. Processed.

Strauss, J., and D. Thomas. 1998. “Health, Nutrition, and Economic Development.” *Journal of Economic Literature* 36(2): 766–817.

United Nations. 1998. *World Population Prospects 1950–2050: Demographic Indicators*. New York: United Nations Population Division.

Weil, D. 2001. “Accounting for the Effect of Health on Economic Growth.” Brown University, Providence, RI. Processed.

World Bank. 1993. *World Development Report 1993: Investing in Health.* Washington, D.C.

_____. 2001. *World Development Indicators 2001*. Washington, D.C.

Young, A. 1994. “Lessons from the East Asian NICS: A Contrarian View.” *European Economic Review* 38(3-4): 964–73.

Young, A. 1995. “The Tyranny of Numbers: Confronting the Statistical Realities of the East Asian Growth Experience.” *Quarterly Journal of Economics* 110(3): 641–80.

Table 1
Panel Growth Regressions

Explanatory Variable	*Coefficient Estimates*			
	1	*2*	*3*	*4*
Capital	0.415** (0.057)	0.460** (0.047)	0.355** (0.072)	0.414** (0.059)
Labor	0.591** (0.068)	0.527** (0.052)	0.660** (0.086)	0.573** (0.065)
Schooling	0.065 (0.046)	0.059 (0.045)	0.129** (0.046)	0.114* (0.048)
Adult survival rate	0.030** (0.009)	0.031** (0.007)	0.021** (0.008)	0.024** (0.007)
Technological catch-up coefficient	0.142** (0.019)	0.150** (0.019)	0.141** (0.027)	0.152** (0.021)
Percentage of land area in the tropics	-0.172 (0.114)	-0.214* (0.102)	-0.193 (0.124)	-0.240* (0.108)
Openness	0.193 (0.117)	0.206* (0.103)	0.195 (0.134)	0.174 (0.110)
Percentage oft land within 100 kilometers of the coast	0.132 (0.133)		0.100 (0.143)	
Ethno-linguistic fractionalization	-0.220 (0.183)		-0.321 (0.202)	
Institutional quality	0.022 (0.026)		0.012 (0.029)	
Test of equality of growth and level coefficients (chi-square d.o.f. under null)	3.59 (4)	6.47 (4)	1.27 (4)	4.90 (4)
Test of over-identifying restrictions (chi square d.o.f. under null)	8.14 (5)	11.33 (8)	7.24 (5)	11.36 (8)
Test for autocorrelation: estimated parameter (standard error)	-0.063* (0.032)	-0.065* (0.029)	-0.038 (0.037)	-0.047 (0.031)
Test that human capital parameters equal calibrated values (chi square d.o.f. under null)	2.23 (2)	3.46 (2)	1.36 (2)	2.24 (2)
Test of constant returns to scale (chi square d.o.f. under null)	0.06 (1)	0.23 (1)	0.19 (1)	0.19 (1)

d.o.f. Degrees of freedom.
* Significant at the 5 percent level.

** Significant at the 1 percent level.
Notes: Robust standard errors are reported in parentheses below coefficient estimates. Number of observations is 416. Year dummies are included throughout.
Source: Authors' calculations.

Table 2. Parameters of Human Capital Variables in Aggregate Production Calibrated from Wage Regressions

Variable	**Calibrated parameter**	**Source**
Years of schooling	0.091	Bils and Klenow (2000) Psacharopoulos (1994)
Adult survival rate	0.0168	Weil (2001)

Source: Authors.