Health, Worker Productivity, and Economic Growth [1]

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Abstract

Microeconomic analyses typically suggest that worker health makes an important contribution to productivity and wages. Weil (2001) uses estimates of the individual-level relationship between health and wages to calibrate an aggregate production function and suggests that differences in health are roughly as important as differences in education in explaining cross-country differences in gross domestic product per worker. We estimate the effect of health on worker productivity directly using cross-country macroeconomic data. We find a positive and significant effect. In addition, the estimated effect of health on aggregate output is consistent with the size of the effect found in microeconomic studies.

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1. Introduction

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

There is also a link 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). These correlations are commonly thought to reflect 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 promote health and longevity, such as a nutritious diet, safe water and sanitation, and quality 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 Graham 2002; Easterlin 1999; Hamoudi and Sachs 1999; World Health Organization 2001). A common empirical approach to study 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, for example, policy variables such as openness to trade and measures of institutional quality, educational attainment, the 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; 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 (see table 1). While the results of empirical growth equations are generally not completely robust (Levine and Renelt 1992), Sala-i-Martin (1997a, 1997b) finds that out of over 32,000 regressions, involving permutations of over 60 variables, initial life expectancy is a positive and significant predictor of economic growth over the period 1960-1992 in excess of 96% of the specifications. This makes initial health one of the most robust predictors of subsequent economic growth that we have.

[insert table 1 about here]

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), who explains output using an aggregate production function and calibrates the parameters of the production function using microeconomic evidence. It has become quite common to use microeconomic evidence on factor shares and the effect of human capital on wages to calibrate production function models of aggregate output (see, for example, Klenow and Rodriguez-Clare 1997; Prescott 1998; Young 1994, 1995). Weil (2001) adds health to the production function and calibrates the effect of adult survival rates on aggregate output.

As a country's health improves and average adult height increases, we would expect to see an improvement in labor productivity and output per worker. However, directly using the relationship between height and productivity at the microeconomic level to predict economic growth at the macroeconomic level is difficult, because we do not have consistent measures of population heights across countries. Weil (2001) overcomes this problem by calculating a relationship between adult height in a population and its adult survival rate (the proportion of 15-year-olds who would live to age 60 at current mortality rates). He shows that adult height and adult 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 can calibrate 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, in developing countries public health measures exist (such as vaccination and antibiotic distribution programs) that can lead to large improvements in health outcomes at relatively low costs (World Bank 1993, World Health Organization 2001). 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 (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 real effect of health 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 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 close to that of Weil (2001) to allow 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 lead to inconsistencies in parameter estimates. In what follows we try to take account of the reverse causality and omitted variable bias. In particular, we try to control for different countries' varying levels of total factor productivity and rates of technological progress. Failure to control for these differences tends to lead to overestimation of the impact of inputs on output, because inputs and productivity levels tend to be positively correlated.[3] We model differences in TFP and technological diffusion using the methods set out in De La Fuente and Domenech (2001) and Bloom, Canning, and Sevilla (2002).

One potential source of omitted variable bias in the production function arises because improved health leads to longer life spans, and this may be reflected in an older work force. A great deal of evidence suggests that wages increase with age and work experience (up to around 30 years of experience according to Psacharopoulos 1994). We allow for this effect by using the age structure and years of schooling of the labor force to calculate the potential stock of experience available to the economy and use this as an input into production. Note that the effect of reduced mortality on experience levels could be counted as a benefit to health, and should be included in its total contribution to gross domestic product (GDP). However, the aim of this paper is to separate out and measure the impact of improved morbidity on labor productivity to generate results that may be compared directly with microeconomic estimates of the link between health and wages. This means that we do not attempt to estimate the indirect impact of health on economic growth via its effect of worker experience, or through labor supply, savings and investment, and school enrollment rates.

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

[3] For example, if two countries have the same savings rate, the one with higher total factor productivity will have a higher gross domestic product and higher total saving, leading to a higher capital stock.

consistent with the calibration approach used by Weil (2001). Indeed, our estimates of the effect of schooling and work experience on GDP are also 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

$$Y = AK^{a}(Lv)^{b} \tag{1}$$

where Y is total 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:

$$w = \frac{dY}{dV} = \boldsymbol{b}\frac{Y}{V} \tag{2}$$

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

$$w_j = wv_j \tag{3}$$

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

$$v_j = \mathrm{e}^{f_s s_j + f_h h_j} \tag{4}$$

where s_j represents years of schooling and h_j represents health. This has the advantage that we can now derive an equation for wages at the individual level:

$$\log w_j = \log(w) + \log(v_j) = \log(w) + f_s s_j + f_h h_j \tag{5}$$

The aggregate production function (1) with our measure of human capital (4) is therefore consistent with the form of the wage equation found at the microeconomic level.

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

$$V = \sum_j v_j = \sum_j \mathrm{e}^{f_s s_j + f_h h_j} \tag{6}$$

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

$$\log V = \log(\sum_j v_j / L) = (\sum_j \log v_j)/L + s^2/2 = \sum_j (f_s s_j + f_h h_j)/L + s^2/2 \qquad (7)$$

and so

$$\log V = f_s s + f_h h + s^2/2 \qquad (8)$$

where s 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 $100 f_s$ percent. This 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 high wage earner also represents a greater investment because it is more costly to produce. The worker must give up the high wage while the extra schooling is taking place.

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 (for instance, Deininger and Squire 1996) they may not be reliable (Atkinson and Brandolini 2001).

Taking logs, our aggregate production function is

$$\log Y = a + a \log K + b(\log L + f_s s + f_h h) \qquad (9)$$

This production function measures human capital by years of schooling and health. In microeconomic wage equations, a second-degree polynomial in worker experience is usually added and normally found to provide a good fit to the data. The corresponding aggregate production function would include experience measures (both average experience and the average of squared experience) as part of human capital along with schooling and health. In our empirical work we investigate adding these additional human capital measures. Table 2 gives the values of the production function parameters on human capital that come from calibration studies based on wage regressions using equation (5), together with their sources. It is conventional to impose constant returns to scale and to calibrate values of around 1/3 for a, the coefficient on capital and 2/3 for b, the coefficient on labor based on the shares of profits and wages in national income (for example, see Hall and Jones (1999)).

[insert table 2 about here]

3. Total Factor Productivity and Economic Growth

Using the aggregate production function (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}, l_{it} are the logs of Y_{it}, K_{it}, 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 (2002) 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.

Since 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 (e.g. see 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 (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:

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

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

This approach to modeling TFP diffusion has been used in cross country production function studies by De La Fuente and Domenech (2001) and Bloom, Canning, and Sevilla (2002) and is formally equivalent to the autoregressive model of TFP used by Griliches and Mairesse (1998) and Blundell and Bond (2000) 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}.[4]

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 testing that 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 Mankiw, Romer, and Weil (1992) and Islam (1995), that take TFP differentials

[4] We could allow the shock to growth in 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. Note that in this case the worldwide productivity ceiling is not identified separately from the effect of worldwide macroeconomic shocks.

across countries to be fixed. The speed of convergence in these models depends on the time it takes for capital stocks 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 e_{it}. We overcome this problem by instrumenting these current input growth rates with lagged input growth rates.[5] We assume that these lagged input growth rates and the lagged levels of inputs are uncorrelated with e_{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, 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 (10). To be valid, shocks to TFP (the error term in our regressions) must not be predicable.

If the shocks to TFP, e_{it}, are correlated over time, lagged endogenous variables that are correlated with $e_{i,t-1}$ or $e_{i,t-2}$ will become correlated with e_{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 (e.g. see 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 $e_{it} = re_{i,t-1} + u_{it}$ where u_{it} is now assumed to be an i.i.d. process. We can now transform equation (15) to give

[5] 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 as well as allowing us to estimate the growth and level effects separately and to test the common factor restriction.

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

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), due to 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, some "common factor" restrictions are imposed by our model: 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 mis-specification.

We model country specific effects on long run steady state TFP using a number of observable country characteristics. It would be desirable to follow 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. 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 fiver 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 were 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 1960-95. Output data (GDP) are obtained from the Penn World Tables version 6.0 (see Summers and Heston 1991 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.

Data on the economically active population are from the International Labour Office (1997). These data report figures only 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 for these years. Our labor supply is given by United Nations estimates of the total economically active population in the given year. Admittedly this is an imperfect measure, because it fails to account for variations across countries in labor force participation, unemployment rates, and hours worked.

Average schooling is measured by a weighted average of the total years of schooling of the male and female populations aged 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 experimented with a number of other options, such as using the weighted averages of the population aged 15 and over, 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). Raw data on adult survival rates (the proportion of 15-year-olds who would reach 60 at current age-specific mortality rates) are taken from the World Bank (2001). Like Weil (2001), we use adult survival rates as a proxy for the health of the work force, even though they measure mortality rates rather than morbidity. 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. This is carried 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 from other measures such as infant mortality (see, for example, Pritchett and Summers 1996 and Bos 1998). We then calculate the average adult survival rate of the economically active population as the weighted average (weighted by share of economically active population) of the estimated sex-specific adult survival rates.

Using the data from the International Labour Office (1997) and our interpolation methods we can determine the labor force for each five-year age-gender group. We construct aggregate experience for each country by computing an experience measure for 22 gender/age group combinations (male and female age groups 15-19, 20-24,...,60-64, 65+). Experience (or more correctly, potential experience) for each group is given by average age minus average years of schooling (the average years of schooling of those aged 15 and older from Barro and Lee 2000), minus six. For simplicity, the average age in each group is taken to be the midpoint of its age range. Average experience in the work force is calculated by using the shares of each group in the total economically active population as weights. Aggregate squared experience is the weighted average of the squared experience of each group.

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 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 wider coverage than the Summers-Heston 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 introduce substantial measurement error, particularly if investment flows do not measure the addition to public capital due to waste and corruption (Pritchett 2000).

We include some country specific variables that may affect the long run level of total factor productivity. 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 on a country's market institutions to some extent) and an indicator for the quality of institutions from Knack and Keefer (1995). We also use the percent of land area in the tropics and a dummy for being landlocked from, Sachs and Mellinger (1999) to control for geography.

Table 3 shows the correlations between the different production function inputs in 1990. Log GDP per worker is highly correlated with log physical capital per worker, adult survival rates, and average years of schooling. However, high log GDP per capita countries tend to have low experience levels (and low experience squared). High levels of schooling mean that workers enter the labor force later, reducing the average experience of the work force. In industrial countries the high adult survival rate and low birth rate results in a relatively large number of older adults in the work force, but this effect is too small to offset the reduction in average experience that comes from higher levels of schooling.

[insert table 3 about here]

Average experience and average experience squared are highly correlated. This is true both in levels and in first differences. While experience varies over a wide range over an individual's life span, the range of the average experience across countries is quite small.

Table 4 shows the pattern of correlation between output and input changes during 1985-90. While output growth and capital stock growth are highly correlated, little relationship is apparent between output growth and the growth of either schooling, adult survival rates, or average experience. The increase in the average years of schooling is negatively correlated with the change in average experience, indicating that extra schooling comes at the cost of lower experience.

[insert table 4 about here]

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. The instruments for columns (1) to (3) are identical and include the lagged growth of capital, labor, schooling, experience, experience squared and the adult survival rate. In column (4) we add the lagged growth of the adult survival rate squared when we try to estimate a non-linear functional form.

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 5 gives estimates of a simple form of the production function including only average years of schooling as our 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 TFP are apparent, with countries in the tropics having lower productivity and open economies having higher productivity.

[insert table 5 about here]

Beneath the parameter estimates we report the results of a number of statistical tests. In each case (except for the autocorrelation test which was discussed above) 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 (i.e., we test that the capital and labor coefficients sum to one). The coefficient on schooling is small and not statistically different from zero; however we 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. One reason for the lack of significance of the schooling variable may be measurement error (see Kruger and Lindhal (2001) and De La Fuente and Domenech (2001)).

We also report three specification tests in column (1). We begin by testing the common factor restrictions in equation (15). 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 5 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), the specification tests are satisfactory, so we cannot reject the validity of the instruments or the common factor restriction implied by our specification.

In column (3) we add both average experience and average experience squared to the model. As expected, the coefficient on experience is positive, while that on experience squared is negative. While both estimates seem large in absolute magnitude, the standard errors are high because of the high correlation between these measures in cross-country data. With individual data experience levels vary widely, but in aggregate data average experience levels (and the average of experience squared) do not vary very much across countries (countries with lower mortality rates tend to have higher levels of schooling) making it difficult to estimate the experience effect precisely.

Testing the four human capital parameters against the calibrated values in table 2 does not reject the null of equality. This implies that our macroeconomic estimates of the effect of our human capital measures on worker productivity are consistent with the results from wage regressions. This model once again passes our specification tests.

One potential issue is that in the first three columns of table 5 is that we assume that the coefficient on the adult survival rate is the same in every country while Bhargava, Jamison, Lau and Murray, 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 5.[6] 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

[6]. In column (4) of table 5 the lagged level of adult survival rate squared instruments itself while we instrument its growth with lagged growth in the adult survival rate squared.

(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 in not statistically significant and we find no evidence that the health effect varies with the level of development.

5. 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 this 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. 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.

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Table 1. Estimates of the Effect of Health on Economic Growth

Study	Health measure (in logs)	Coefficient (standard error)	Growth Effect of increasing year life expectancy by 5 years	Data	Estimator	Other Covariates (all papers have the log of initial income per capita or per worker)
Barro (1996)	Life expectancy	0.042 (0.014)	0.33	Three periods 1965-75, n = 80; 1975-85 n = 87; 1985-90, n = 84	3SLS using lagged values of some regressions as instruments, period random effects	Male secondary and higher schooling, log(GDP)*male schooling, log fertility rate, government consumption ratio, rule of law index, terms of trade change, democracy index, democracy index squared, inflation rate, continental dummies
Barro and Lee (1994)	Life expectancy	0.073 (0.013)	0.58	Two periods, n = 85 for 1965-75, n = 95 for 1975-85	SUR with country random effects	Male and female secondary schooling, I/GDP, G/GDP, log(1+black market premium), revolutions
Barro and Sala-i-Martin (1995)	Life expectancy	0.058 (0.013)	0.46	Two periods, n = 87 for 1965-75, n = 97 for 1975-85	SUR with country random effects	Male and female secondary and higher education, log(GDP)*human capital, public spending on education/GDP, Investment/GDP, government consumption/GDP, log(1 + black market premium), political instability, growth rate in terms of trade

Bhargava and others (2001)	Adult survival Rate ASR*log(GDPC)	0.358 (0.114) -0.048 (0.016)	N.A.	25-year panel at 5-year intervals, 1965-90, n = 92	Dynamic random effects	Tropics, openness, log fertility, log (Iinvestment/GDP)
Bloom, Canning, and Malaney (2000)	Life expectancy	0.063 (0.016)	0.50	25-year panel at 5-year intervals, 1965-90, n = 391	Pooled OLS	GDP per worker, tropics, landlocked, institutional quality, openness, log of years of secondary schooling, population growth, working-age population growth, log ratio of working-age to total population, population density, period dummies
Bloom and Malaney, (1998)	Life expectancy	0.027 (0.107)	0.21	25-year cross-section, 1965-90, n = 77	OLS	Population growth, growth of economically active populations, log years of secondary schooling, natural resource abundance, openness, institutional quality, access to ports, average government savings, tropics, ratio of coastline distance to land area
Bloom and others (1999)	Life expectancy	0.019 (0.012)	0.15	25-year cross-section, 1965-90, n = 80	2SLS	Log of ratio of total population to working-age population, tropics, log of years of secondary schooling, openness, institutional quality, population growth rate, working-age population growth rate
Bloom and Sachs (1998)	Life expectancy	0.037 (0.011)	0.29	25-year cross-section, 1965-90, n = 65	OLS	Log secondary schooling, openness, institutional quality, central government deficit, percentage area in tropics, log coastal population density, log inland population density, total population growth rate, working-age population growth rate, Africa dummy

Bloom and Williamson (1998)	Life expectancy	0.040 (0.010)	0.32	25-year cross-section, 1965-90, n = 78	OLS	Population growth rate, working-age population growth rate, log years of secondary schooling, natural resource abundance, openness, institutional quality, access to port, average government savings rate, tropics dummy, ratio of coastline to land area
Caselli, Esquivel, and Lefort (1996)	Life expectancy	-0.001 (0.032)	0.00	25-year panel at 5-year intervals, 1960-85, n = 91	GMM (Arellano-Bond method)	Male and female schooling, I/GDP, G/GDP, black market premium, revolutions
Gallup and Sachs (2000)	Life expectancy	0.030 (0.009)	0.24	25-year cross-section, 1965-90, n = 75	OLS	Years of secondary schooling, openness, quality of public institutions, population within 100 kilometers of the coast, malaria index in 1966, change in malaria index from 1966-1994
Hamoudi and Sachs (1999)	Life expectancy	0.072 (0.020)	0.57	15-year cross section, 1980-95, n = 78	OLS	Institutional quality, openness, net government savings, tropics land area, log coastal population density, population growth rate, working-age population growth rate, Africa dummy
Sachs and Warner (1997)	Life Expectancy Life Expectancy squared	45.48 (17.49) -5.40 (2.24)	0.06	25-yr cross section, n = 79	OLS	openness, openness*log(GDP), land-locked, government saving, tropical climate, institutional quality, natural resource exports, growth in economically active population minus population growth

ASR: adult survival rate
GDP Gross domestic product.
GMM: Generalized method of moments
OLS Ordinary least squares.
3SLS: Three stage least squares
SUR: seemingly unrelated regression

Note: The growth effects of a 5 year increase in life expectancy are calculated for a country with a life expectancy of 63, the average life expectancy in developing countries in 1990.
Source: Authors.

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)
Potential experience	0.051	Bils and Klenow (2000) Psacharopoulos (1994)
Potential experience squared	-0.0007	Bils and Klenow (2000) Psacharopoulos (1994)
Adult survival rate	0.0168	Weil (2001)

Source: Authors.

Table 3. Correlation in Levels 1990

Variable	Log output per worker	Log capital per worker	Adult survival rate	Average years of schooling	Average experience
Log capital per worker	0.977	1.000			
Adult survival rate	0.878	0.879	1.000		
Average years of schooling	0.858	0.865	0.806	1.000	
Average experience	-0.279	-0.277	-0.252	-0.464	1.000
Average experience squared	-0.452	-0.448	-0.420	-0.577	0.960

Source: Authors' calculations.

Table 4. Correlation in Changes, 1985-90

Variable	Log output per worker	Log capital per worker	Adult survival rate	Average years of schooling	Average experience
Log capital per worker	0.665	1.000			
Adult survival rate	-0.048	-0.053	1.000		
Average years of schooling	0.132	0.221	-0.101	1.000	
Average experience	0.017	0.013	0.153	-0.641	1.000
Average experience squared	-0.025	-0.039	0.188	-0.633	0.976

Source: Authors' calculations.

Table 5
Panel Growth Regressions

	Coefficient Estimates			
Regression Explanatory Variable	1	2	3	4
Capital	0.490** (0.045)	0.443** (0.044)	0.400** (0.051)	0.388** (0.062)
Labor	0.514** (0.056)	0.549* (0.052)	0.600** (0.063)	0.617** (0.075)
Schooling	0.014 (0.055)	-0.035 (0.050)	0.008 (0.051)	0.013 (0.043)
Adult survival rate		0.030** (0.007)	0.022** (0.008)	-0.019 (0.058)
Adult survival rate^2				0.0003 (0.0020)
Experience			0.260* (0.116)	0.221* (0.104)
Experience^2			-0.005* (0.002)	-0.005* (0.002)
Technological catch-up coefficient	0.121** (0.021)	0.139** (0.021)	0.133** (0.021)	0.136** (0.019)
Percentage of land area in the tropics	-0.288* (0.124)	-0.271* (0.109)	-0.254* (0.122)	-0.217 (0.119)
Openness	0.352* (0.143)	0.289* (0.119)	0.277* (0.128)	0.254* (0.129)
Test: equality of growth and level coefficients (chi-square d.o.f. under null)	4.29 (3)	6.66 (4)	6.17 (6)	5.11 (7)
Test of overidentifying restrictions (chi square d.o.f. under null)	32.52** (13)	15.87 (12)	10.54 (10)	14.69 (11)
Test for autocorrelation: estimated parameter (standard error)	-0.097** (0.032)	-0.060 (0.034)	-0.051 (0.037)	-0.054 (0.037)
Test: human capital parameters equal calibrated values (chi square d.o.f. under null)	2.26 (1)	3.76 (2)	8.19 (4)	
Test of constant returns to scale (chi square d.o.f. under null)	0.00 (1)	0.07 (1)	0.00 (1)	0.03 (1)

d.o.f.: degrees of freedom, * denotes significance at the 5 percent level, ** denotes significance at the 1 percent level. Robust standard errors are reported in parentheses below coefficient estimates. *Note:* 416 observations. Year dummies are included throughout. *Source:* Authors' calculations.