# A Contribution to the Empirics of Total Factor Productivity*

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**Abstract**

Our paper analyzes the causal links between human capital accumulation and growth in total factor productivity (TFP). In particular, it tests the Nelson-Phelps hypothesis that human capital is crucial in enabling the imitation of technologies developed at the frontier. To this end we calculate TFP for a sample of 86 heterogeneous countries over the period 1960-1990 and investigate whether there has been (conditional) convergence in TFP. Our regressions use a variety of GMM estimators in a dynamic panel framework with fixed effects. Human capital is found to have a positive and significant effect on the long run growth path of TFP. Countries are found to be converging to these growth paths at a rate of about 3% a year. This work goes some way in resolving the debate over whether factor accumulation or TFP increases are more important for economic growth; while TFP differences explain most of the static variation in GDP across countries, human capital accumulation is a crucial determinant of the dynamic path of TFP

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## Introduction

Over the last decade there has been a lively debate as to whether it is differences in factor accumulation or in total factor productivity (TFP) that are mainly responsible for the observed variation in per capita incomes across countries. This paper argues that the dichotomy is spurious, resting on a conflation of the proximate determinants of income variation with the ultimate determinants of the same.

Two important recent contributions to the debate are Klenow and Rodriguez-Clare (1997) and Hall and Jones (1999). They utilize microeconomic evidence on the private returns to physical and human capital in an accounting framework and conclude that productivity accounts for the majority of cross country income differences. This accounting approach neglects the possibility of spillovers between factor accumulation and productivity. If the social return to capital is higher than the private return, the accounting framework will giver higher weight to productivity differences in explaining income variation, even though the ultimate cause of the variation is factor accumulation.

This paper attempts to empirically establish the linkage between factor accumulation and total factor productivity. We suggest that the key to understanding productivity growth in most countries is through technology spillovers from the handful of countries that perform R&D. These spillovers are contingent on a domestic stock of human capital sufficient to take advantage of products and techniques developed elsewhere. Human capital affects these spillovers in a dynamic manner, so that an increase in human capital intensity today has an impact on TFP in all subsequent periods, not just the current one.

Our model is based on three assumptions about spillovers. First, for most countries the technological frontier is expanding exogenously. Second, the ability of a country to take advantage of technological spillovers is a function of its stock of human capital. In the long run, countries with more educated work forces will be closer to the technological frontier. Third, movement to the long run growth path of productivity is not immediate. To use the language of the traditional empirical growth literature, our model is one of conditional convergence in TFP, where the long run level of TFP relative to the frontier is determined by the level of human capital.

Empirically we establish that for a large and heterogeneous sample of developing countries human capital has a large and significant positive effect on the long run TFP growth path. This effect is not immediate; convergence toward the long run growth path is at a rate of about 3% per year. Increases in human capital stocks will therefore significantly increase the growth rate of productivity for several decades following the change.

This result has important consequences for the factor accumulation versus productivity debate. It is well established that in a static accounting framework most of the difference in income between countries is attributable to TFP (we show that this is true for our sample at every point in time). By focusing on convergence in TFP rather than the standard paradigm of income convergence, we can demonstrate the dynamic effect of human capital on productivity growth. It follows that while the proximate cause of differences between countries appears to be productivity, the ultimate cause may be varying levels of human capital. In fact we find that human capital can account for the vast majority of the long run differences in productivity levels.

# 1 Literature Review

## 1.1 Growth Empirics

Mankiw, Romer and Weil (1992) purported to show that the Solow model, when augmented to include human capital as a factor of production, did a reasonable job of explaining the variations in per capita real income that are observed across a large and heterogeneous sample of countries. They found that factor accumulation could account for a majority of differences in income per capita under the assumption that all countries shared a common level of productivity.

However, their crucial assumption that all countries enjoy identical levels of productivity has been challenged by a series of panel studies such as Knight, Loyaza and Villanueva (1993), Islam (1995) and Caselli, Esquivel and Lefort (1996). This body of work demonstrates that while the income-convergence predicted by neoclassical growth models is indeed taking place, this convergence is conditional on differing levels of productivity across countries. Since these studies are carried out in a fixed-effects panel framework, their estimates for the country-specific fixed effects can be interpreted as a measure of technology broadly defined, or TFP. They find that differences in technology are pervasive and important in determining steady states.

These panel results suggest that an analysis of why countries differ so much in their technologies and of how differences in technology between countries have evolved is essential. Unfortunately, panel studies of the kind carried out by Islam and Caselli et al. (1996) cannot, by their nature, show the evolution of differences in technology, since only a single fixed effect is recovered for each country. Although they allow for differences in productivity across nations, they are forced to assume that each country's relative productivity remains entirely unchanged over the sample period.

With the increased focus on productivity, several recent papers have concentrated on calculating TFP for a large sample of countries at a single point in time. TFP is calculated as a Solow residual from real income per capita, after accounting for the contribution of various factors of production. Klenow and Rodriguez-Clare (1997) calculate TFP for a sample of countries after accounting for the contributions made by labor, physical capital and human capital. They then decompose the variance of per capita income into that attributable to differences in factors of production and that attributable to differences in TFP. Using a number of formulations they conclude that, in general, differences in TFP play a greater role.[1] Their results are corroborated by Hall and Jones (1999), who find, again, that the lion's share of the variation in incomes across the world is explained by differences in TFP, not in factors of production.

## 1.2 Technological Spillovers and Human Capital

Our empirical focus on the evolution of TFP has its counterpart in the many theories of technological change that are the focus of the recent growth literature. Grossman and Helpman (1991) and Aghion and Howitt (1992) are two benchmark contributions that describe economies in which purposive research and development is the engine that drives technical progress.

However, empirical evidence suggests that most research and development is concentrated in a handful of rich countries, so that these models are of limited relevance in describing the evolution of TFP in the vast majority of nations. It seems more promising to consider models that emphasize the ability of "follower" countries to imitate the innovations carried out in "leader" countries. Various factors may be thought to influence the efficacy with which such imitation may be carried out, such as the degree to which a country is open to dealings with the rest of the world (because an open country is able to take advantage of imports from countries that do perform R&D, and also to foreign direct investment from firms at the world technological frontier), and the social, legal and geographical features peculiar to that country. Another crucial factor in determining the ease of imitation, which this paper concentrates on, is the stock of human capital per worker in a given country.

The notion that the stock of human capital is a crucial determinant of the ability of a backward country to adopt technologies from the technological frontier has a long pedigree, dating back to Nelson and Phelps (1966). Microeconomic evidence

[1] Klenow and Rodriguez-Clare (1997) find that productivity differences may account for 67% of differences in income per worker, compared to only 22% for Mankiw et al. (1992)

for the proposition that more educated workers have a comparative advantage in the implementation of new technologies comes from Foster and Rosenzweig (1995), Wozniak (1984) and Bartel and Lichtenberg (1987). More recently several empirical papers, such as Benhabib and Speigel (1994), have argued that the relationship between human capital and income growth is best viewed in the context of the positive effect that human capital has on TFP, rather than its direct effect as an accumulable factor in the production function.

Bils and Klenow (2000) argue that microeconomic evidence on returns to schooling is inconsistent with the large and positive coefficients on human capital found in growth regressions by Barro (1991); this, too, suggests that human capital impacts income through the separate channel of TFP. Borensztein, De Gregorio and Lee (1998) regress GDP growth rates on both foreign direct investment (FDI) and a term that interacts FDI with human capital. They find that while the coefficient on FDI by itself is negative, the coefficient on the interactive term is positive and significant, suggesting that human capital is essential to the process of technological diffusion through FDI.

Our paper aims to directly estimate the importance of human capital in enabling technological imitation and thereby inducing productivity growth. To this end we calculate Solow residuals for a large sample of countries over a thirty year period and then examine the evolution of these residuals. Particular attention is paid to the issue of whether TFP is converging, and whether human capital stocks affect the steady state growth path of TFP toward which each country is converging.

Our working hypothesis is that the rate of growth of a country's TFP is a positive function of the gap between its actual TFP level at point in time, and its potential TFP level. The potential level of TFP is a function of three things. First, the country's stock of human capital per worker: the higher it is, the greater is the imitation possible. Second, the level of TFP at the world technological frontier: the higher it is, the more the ideas available to imitate. And third, a country specific fixed effect capturing, for example, institutional and geographical heterogeneity that does not change through the sample period. From this hypothesis we derive an empirical specification that consists of a fixed-effects dynamic panel regression, which we proceed to estimate using our panel of TFP figures. To preview our results, we find that countries converge to their individual TFP growth paths at about 3% per year. Human capital stocks have a positive and significant effect on each country's long run TFP level relative to the frontier. We further find that a large share of the long run variation in TFP across countries is attributable to variation in human capital stocks.

The next section of our paper describes the methodology we use to obtain our panel of TFP figures, the sources that we use in our calculations, and some of the patterns in the data that become evident. Section 3 sketches a simple model from which our empirical specification is derived. Section 4 describes and briefly reviews the econometric techniques that we employ. Section 5 contains our main empirical results. Section 6 presents some additional results. The subsequent section concludes.

# 2 Calculating Total Factor Productivity

## 2.1 Methodology and Data

Our methodology for calculating TFP follows recent work by Klenow and Rodriguez-Clare (1997) (KRC) and Hall and Jones (1999). We assume that the aggregate production function takes a simple Cobb-Douglas form and then calculate TFP as a Solow residual.[2]

$$Y_i = K_i^{\alpha}(A_i H_i)^{1-\alpha} \tag{1}$$

[2] Aiyar and Dalgaard (2002) establish that for international TFP comparisons a Cobb-Douglas production function with a capital share of one third is a very close approximation to more general functional forms that need not assume a constant elasticity of substitution between factors.

Country $i$ produces output $Y_i$ using its stock of physical capital $K_i$ and its stock of human capital $H_i$. $A_i$ is a measure of productivity in that country, indexing how efficiently it is turning its inputs into outputs. The country's human capital stock is defined in the following way:

$$H_i = e^{\mu(E_i)} L_i \tag{2}$$

where the size of the labor force is multiplied by the average efficiency units embodied in the workers that comprise the labor force. $E_i$ denotes the average years of schooling attained by a worker in country $i$, and the derivative $\mu'(E)$ is the return to education estimated in a Mincerian wage regression. $\mu(0) = 0$, so that a person with no education owns only the single efficiency unit comprised of her raw labor, while a person with E years of education owns $e^{\mu(E)}$ efficiency units of labor.[3]

Defining $y = Y/L$ and $h = H/L$ we can rewrite the production function in terms of output per worker as:

$$y_i = A_i \left(\frac{K}{Y}\right)_i^{\frac{\alpha}{1-\alpha}} h_i \tag{3}$$

This formulation enables us to calculate $A_i$ as a residual once we have data on income per worker, human capital per worker, the capital-output ratio of the economy, and the share of physical capital in output.

Our data on GDP per worker are from the Penn World Tables 5.6, and our series for capital per worker is taken from Easterly and Levine (2000).[4] Before calculating TFP, we make an adjustment to correct for the use of natural resources: we subtract

[3]Following Hall and Jones (1999), $\mu(E)$ is assumed to be piecewise linear, with a coefficient of 13.4 for the first 4 years of schooling, 10.1 for the second four years of schooling, and 6.8 for schooling beyond the 8th year. The coefficient on the first four years is taken from to the return to an additional year of schooling in sub-Saharan Africa. The coefficient on the second four years is the average return to an additional year of schooling worldwide. The coefficient on schooling above eight years is taken from the average return to an additional year in the OECD. All three coefficients are from Psacharopoulos (1994) .

[4]both data sets are available from the World Bank website (http://www.wordbank.org/research/growth). All figures are in PPP adjusted international dollars.

from GDP the share of it that is attributable to Mining and Quarrying in national income accounts, using data from UN publications.[5]

Finally, we assume that $\alpha = 1/3$, as is standard in the literature.[6] We are then able to obtain TFP figures for a complete five-year panel from 1960 to 1990, for a sample of 86 countries. Table 1 shows TFP for some representative countries for the years 1960, 1975 and 1990 (see Appendix D for our complete panel of figures). To facilitate comparison, all figures are normalized by the 1960 TFP level of the USA.

Table 1: The Evolution of TFP for a Selection of Countries

| Country | $\frac{A_{i,1960}}{A_{USA,1960}}$ | | $\frac{A_{i,1975}}{A_{USA,1960}}$ | | $\frac{A_{i,1990}}{A_{USA,1960}}$ | |
|---|---|---|---|---|---|---|
| Romania | 0.04 | (86) | 0.12 | (86) | 0.15 | (82) |
| Kenya | 0.13 | (82) | 0.21 | (80) | 0.19 | (79) |
| India | 0.26 | (71) | 0.22 | (79) | 0.30 | (67) |
| Hong Kong | 0.28 | (66) | 0.68 | (41) | 1.24 | (7) |
| Japan | 0.31 | (62) | 0.58 | (50) | 0.79 | (34) |
| Singapore | 0.40 | (50) | 0.90 | (22) | 1.33 | (3) |
| Brazil | 0.52 | (37) | 0.98 | (18) | 0.78 | (35) |
| Columbia | 0.45 | (45) | 0.67 | (43) | 0.69 | (42) |
| Germany | 0.61 | (32) | 0.87 | (26) | 1.13 | (13) |
| Canada | 0.79 | (15) | 1.07 | (13) | 1.17 | (11) |
| U.K. | 0.81 | (13) | 0.91 | (21) | 1.18 | (10) |
| U.S.A. | 1.00 | (6) | 1.10 | (10) | 1.19 | (9) |
| World Average | 0.51 | | 0.69 | | 0.67 | |
| OECD Average | 0.68 | | 0.93 | | 1.06 | |

Rank in Parenthesis

[5]Since TFP is calculated as a residual, we want to ensure that it reflects value added after accounting for factors of production, rather than simply resource-wealth. Not making the adjustment leads to implausibly high values of TFP for countries that are rich in oil or minerals, as noted previously by Hall and Jones (1999) In addition, mining income is very volatile over time. If left uncorrected, swings in natural resource prices would induce large movements in the measured TFP of countries with significant mining output. In order to carry out our adjustment we needed data on the share of mining in all our sample countries in 1960, 1965, and so on up to 1990. Unfortunately the UN data has some gaps; and we have to extrapolate values for the mining shares of some countries in some years. Our extrapolation procedures are discussed in Appendix B. Section 6 discusses the impact of our correction procedure on our results.

[6]Gollin (2002) provides evidence that assuming a heterogeneous share of capital is sensible.

The lowest TFP in our sample belonged to Romania for most of our thirty year period, although in general a group of sub-Saharan African countries brought up the rear. West European countries, together with Canada and the US, clustered near the top of the rankings for most of the period. The distribution of the worst-off countries remained worryingly static; of the 10 lowest ranked countries in 1960, 8 remained in the bottom 10 in 1990. On the other hand there was spectacular movement for some countries which started out in the middle. The success of East Asia stands out. Hong Kong moved up an incredible 59 places in the rankings, registering an average growth rate of TFP of almost 5% per year over the period, while Singapore moved up 47 places with a 4% per year growth rate.[7] At the other end of the spectrum, Guyana registered negative productivity growth at an average of 3.8% per year, while Nicaragua, Iran and Haiti registered negative growth of over 2% per year.

## 2.2 Variance Decomposition

As a final preliminary exercise, it is of interest to perform a decomposition (in logs) of the variance of GDP per capita into the variance of the factors of production on the one hand, and TFP on the other, in the manner of Klenow and Rodriguez-Clare (1997). Define

$$X_i = \left(\frac{K_i}{Y_i}\right)^{\frac{\alpha}{1-\alpha}} h_i \tag{4}$$

Substituting into the production function and taking logs,

$$\log y_i = \log A_i + \log X_i \tag{5}$$

[7]Our results for Singapore stand in contrast to those of Young (1994) and Young (1995). Using more disaggregated data, Young suggested that Singapore and other Asian tigers grew mainly through factor accumulation, not productivity growth. Our formulation however, is closer to that of Klenow and Rodriguez-Clare (1997), and like them we find high rates of TFP growth for East Asia and especially Singapore. One crucial difference between Young's analysis and ours is that we are trying to explain growth in output per capita, not growth in output. Secondly, capital accumulation that is *induced* by growth in TFP should be ascribed to productivity, not factor-accumulation. Like Klenow and Rodriguez-Clare (1997), we explicitly recognize this in our production function by measuring capital accumulation in terms of changes in the capital-output *ratio*.

$$\frac{var(\log y_i)}{var(\log y_i)} = \frac{cov(\log y_i, \log A_i)}{var(\log y_i)} + \frac{cov(\log y_i, \log X_i)}{var(\log y_i)} = 1 \tag{6}$$

This "split" gives us an idea of how much of the static variation in income can be attributed to the variation in TFP, and how much laid at the door of factor variations. Of course, this decomposition is equivalent to examining the OLS coefficients from separate regressions of $\log A_i$ and $\log X_i$ respectively on $\log y_i$. Thus, as Klenow and Rodriguez-Clare (1997) point out, the decomposition amounts to asking how much higher our conditional expectation of $A$ (or $X$) is, if we observe a 1% higher $y$ in a country relative to the mean of all countries. Table 2 shows the results of this decomposition by year.

Table 2: Variance Decomposition of Log Incomes by Year

| | $cov[\log(y), \log(Z)]/var \log(y)$ | | | |
|---|---|---|---|---|
| Year | $Z = \left(\frac{K}{Y}\right)^{\frac{\alpha}{1-\alpha}}$ | $Z = h$ | $Z = X$ | $Z = A$ |
| 1960 | 0.186 | 0.230 | 0.416 | 0.586 |
| 1965 | 0.190 | 0.227 | 0.417 | 0.583 |
| 1970 | 0.190 | 0.238 | 0.427 | 0.573 |
| 1975 | 0.206 | 0.246 | 0.452 | 0.548 |
| 1980 | 0.190 | 0.255 | 0.445 | 0.555 |
| 1985 | 0.184 | 0.249 | 0.432 | 0.568 |
| 1990 | 0.170 | 0.238 | 0.408 | 0.592 |

It is apparent that the decomposition has remained rather stable over the years, ranging from a 41% - 59% split between factors of production in 1990 and TFP to a 45% - 55% split in 1975 at the extremes. We therefore confirm that differences in TFP explain the better part of the static variation in income between countries for every year in our sample. Accordingly, the next section develops our hypotheses about the evolution of TFP and derives the empirical specification that we use in estimation.

## 3 The Model

We start with a working hypothesis in the spirit of Nelson and Phelps (1966), which captures the idea that the rate of change of TFP in a country is positively related to the size of the gap between its actual TFP at a point in time, and its potential TFP at the same moment in time.

$$\frac{\dot{A}}{A}(t) = \lambda(\log A^*(t) - \log A(t)) \tag{7}$$

In the above formulation, $A^*(t)$ represents the country's potential level of TFP at time t, and we hypothesize that it is determined in the following way:

$$A^*(t) = Fh^{\phi}T(t) \tag{8}$$

where $F$ is an index of fixed factors specific to the country, and $T(t)$ is an index of technology which grows exogenously over time.[8]

It is apparent that in our formulation $\phi$ represents the elasticity of the potential TFP level of a country with respect to its stock of human capital per worker, while $\lambda$ is the coefficient of conditional convergence (i.e. an economy closes half the gap between its current and potential level of TFP in $\log 2/\lambda$ years).

Noting that $\dot{A}/A$ is the time derivative of $\log A$, multiplying equation (7) through by $e^{\lambda t}$ and rearranging terms allows us to obtain:

$$e^{\lambda t}([\log \dot{A}(t)] + \lambda \log A(t)) = e^{\lambda t}\lambda(\log F + \phi \log h + \log T(t)) \tag{9}$$

[8] Exogenous technological improvement means that the potential TFP level is always rising. As long as the level of human capital is monotonically increasing, all countries will remain below their potential at all times.

It follows that:

$$\int_{t_1}^{t_2} e^{\lambda t}([\log \dot{A}(t)] + \lambda \log A(t))dt = \log F \int_{t_1}^{t_2} \lambda e^{\lambda t} dt + \phi \log h \int_{t_1}^{t_2} \lambda e^{\lambda t} dt$$
$$+ \int_{t_1}^{t_2} e^{\lambda t} \log T(t) dt \tag{10}$$

Finally, performing the integration in (10), multiplying through by $e^{-\lambda t_2}$ and rearranging terms yields:[9]

$$\log A(t_2) = e^{-\lambda\tau} \log A(t_1) + \phi(1 - e^{-\lambda\tau}) \log h + (1 - e^{-\lambda\tau}) \log F$$
$$+ e^{-\lambda t_2} \int_{t_1}^{t_2} e^{\lambda t} \log T(t) dt \tag{11}$$

where $\tau = (t_2 - t_1)$. Equation (11) falls neatly into the class of dynamic panel models with a fixed effect and a time trend. To see this, define:

$$\begin{aligned}
a_{i,t} &= \log A(t_2) \\
a_{i,t-1} &= \log A(t_1) \\
x_{i,t-1} &= \log h(t_1) \\
f_i &= (1 - e^{-\lambda\tau}) \log F \\
\beta &= \phi(1 - e^{-\lambda\tau}) \\
\rho &= e^{-\lambda\tau} \\
\eta_t &= e^{-\lambda t_2} \int_{t_1}^{t_2} e^{\lambda t} \log T(t) dt
\end{aligned} \tag{12}$$

[9]Note that the way in which we specify h implicitly assumes that it is constant between the limits of integration $t_1$ and $t_2$. This is a standard ploy in the panel estimation of growth regressions. For example in Islam (1995) and Caselli et al. (1996), variables such as the savings rate, the population growth rate, and the stock of human capital are assumed to stay constant within each five year period, but shift lumpily between periods. In effect a variable that is evolving continuously in reality is constrained to change discretely, at fixed intervals. This is one of the reasons that Islam (1995) and Caselli et al. (1996) (and our own study) use short five year panels rather than the ten year panels used by other researchers.

Then, with the addition of a disturbance term, we can write (11) as:

$$a_{i,t} = f_i + \rho \ a_{i,t-1} + \beta x_{i,t-1} + \eta_t + u_{i,t} \tag{13}$$

where $f_i$ is a country specific fixed effect, $\eta_t$ is a time trend that is common to all countries, and $u_{i,t}$ is the random error term. It is apparent that $\lambda$ and $\phi$ are easily recovered from the coefficients $\rho$ and $\beta$ respectively. We use equation (13) for estimation.

Note that the way in which we have specified our model is partly driven by the data we have available to us. In particular, we are forced to ignore several interesting hypotheses about the determinants of a country's potential TFP level due to lack of suitable panel data. For example, the recent growth literature emphasizes that factor productivity may be driven by the import of products from countries that perform R&D in their own right. Coe and Helpman (1995) test this hypothesis for a small sample of OECD countries for which data are available on the R&D stocks of each country and on the share of each country's products in the total imports of every other country.[10] Were this data available for our panel, we could have added an index of the R&D stocks of trading partners weighted by import shares to our determinants of potential productivity. A similar exercise could have been undertaken with respect to FDI as a share of GDP, or with respect to an index of the R&D stocks of international investors weighted by FDI shares, but, again, the non-comprehensive nature of available data prevents us from doing so. It may be argued that these other channels of technological diffusion are subsumed in our country-specific fixed effect, but of course this holds true only to the extent that FDI and imports as a proportion of GDP and the composition of a country's trade and investment partners stay unchanged over the thirty year period that we examine.

[10] Although Coe and Helpman (1995) find that both the absolute volume of imports and the composition of a country's trade-partners are significant in explaining TFP, see Keller (1998) for a rebuttal of the latter claim and Coe and Hoffmaister (1999) for a response.

Our model is one of technology adoption and the movement of the technological frontier is assumed to be exogenously determined. The model may not be appropriate for countries that produce new technologies. For this reason, our main results in section 5 focus on the 64 non-OECD countries in our sample. Results from the full sample do not contradict our main results and are reported in section 6.

# 4 Estimation Procedure

In the previous section we derived a regression specification of the form[11]

$$a_{i,t} = f_i + \rho\ a_{i,t-1} + \beta x_{i,t-1} + \eta_t + u_{i,t}, \quad i = 1 \ldots N, \quad t = 2 \ldots T \tag{14}$$

We estimate (14) using an application of the generalized method of moments estimator (GMM) for dynamic panels suggested by Arellano and Bond (1991) and familiar to the empirical growth literature through Caselli et al. (1996). GMM estimation is appropriate in this context because it is capable of addressing two econometric problems with the estimation of (14). It produces consistent estimates in the presence of a lagged dependent variable and it allows for varying degrees of endogeneity in the explanatory variables.

In order to estimate (14) we must perform two transformations. First, to eliminate the time varying component all variables are measured as deviations from their period specific means, $\tilde{x}_{i,t} = x_{i,t} - \sum_{i=1}^{N} x_{i,t}/N$. Second, the first difference is taken to remove the country- specific effects.

$$\tilde{a}_{i,t} - \tilde{a}_{i,t-1} = \rho(\tilde{a}_{i,t-1} - \tilde{a}_{i,t-2}) + \beta(\tilde{x}_{i,t-1} - \tilde{x}_{i,t-2}) + (\widetilde{u}_{i,t} - \widetilde{u}_{i,t-1}) \tag{15}$$

$$i = 1 \ldots N, \quad t = 3 \ldots T$$

[11] T is measured as the number of time periods for which $a_{i,t}$ observations exist. The index $t$ begins at one. Because equation (14) requires lagged values, it can only be estimated beginning in period two

This equation cannot be estimated by OLS because $\tilde{a}_{i,t-1}$ is correlated with $\widetilde{u}_{i,t-1}$. For this reason, the lagged dependent variable term must be instrumented. Lagged values of the dependent variable are valid instruments under the assumption that $E(\tilde{a}_{i,s}\ \widetilde{u}_{i,t}) = 0$ for all $s \leq t-1$. This assumption requires that there is no serial correlation in the error terms, i.e. $E(\widetilde{u}_{i,t}\widetilde{u}_{i,t-1}) = 0$.[12] Our estimation procedure utilizes all valid $y$ instruments for each time period.

There is also the potential problem of endogeneity, arising from the fact that $\tilde{x}_{i,t-1}$ may be correlated with $\widetilde{u}_{i,t-1}$. Because our explanatory variable, the log of human capital, is a stock variable, we will assume that $\tilde{x}_{i,t}$ is predetermined at time $t$ such that $E(\tilde{x}_{i,s}\ \widetilde{u}_{i,t}) = 0$ for all $s \leq t$. Both this assumption as well as the assumption concerning the absence of correlation in the error terms are tested later.

The moment restrictions exploited by our GMM estimation procedure are:

$$
\begin{aligned}
E(\tilde{a}_{i,s}\ \widetilde{u}_{i,t}) &= 0, \quad s \leq t-1 \\
E(\tilde{x}_{i,s}\ \widetilde{u}_{i,t}) &= 0, \quad s \leq t
\end{aligned}
\tag{16}
$$

These are the assumptions embodied in our preferred GMM estimator, which we label GMMa, and which we will argue is the most appropriate for the investigation at hand. All lags of $a$ which are valid instruments are employed, as are all orthogonal lags of the $x$ observations.

Our second estimator is labelled GMMb, and it too utilizes all valid lags of $a$. It differs from GMMa in that the differenced $x$ values are instrumented on themselves, without using any additional lags as instruments. This estimator also requires the predeterminacy of $x$. We employ this estimator because there are some Monte Carlo simulations that indicate that while additional $x$ instruments always increase the efficiency of the GMM procedure, they may increase bias in short panels.

[12] Although for notational simplicity we are indexing time in unit increments, recall that our base time-interval is 5 years. In annual terms, we assume that there is no fifth order serial correlation in the error term.

Our third instrumentation scheme, labeled GMMc, is identical to the first, except that the most recent $x$ observation is dropped from the instrument set. This is equivalent to relaxing the predeterminacy assumption on $x$ by one period, so that $E(\tilde{x}_{i,t}\ \widetilde{u}_{i,t}) \neq 0$ is allowed. This estimation is performed primarily as a test of the stronger predeterminacy assumption.

All our estimates are accompanied by the Sargan test statistic to check the validity of our overidentifying restrictions, and the $m2$ test statistic described in Arellano and Bond (1991). The latter statistic checks for second-order serial correlation in the errors of the equation in first-differences, which must be absent if our assumption of no serial correlation in the model in levels is correct. Under the null hypothesis that there is no serial correlation, $m2$ is distributed as a standard normal statistic. Note that if our tests reject serial correlation in general, they also reject it for the special case in which such correlation is generated by business-cycle effects.

Our estimation procedures are discussed in greater detail in Appendix C.

# 5 Results

## 5.1 Base Results

The results for the non-OECD sample are reported in Table 3. The reduced form coefficients $\rho$ and $\beta$ are significant at the 1% level for all three regressions. The coefficient on lagged productivity, our estimator for convergence, is significantly different from unity at the 1% level for the more efficient estimators, GMMa and GMMc.

For all three regressions, the Sargan test of overidentifying restrictions indicates that we cannot reject the hypothesis that our identification assumptions are valid. Similarly, the values of the m2 statistic support our assumption that the errors in the levels model are not serially correlated.

Table 3: Regression Results – non-OECD countries

| | GMMa | GMMb | GMMc |
|---|---|---|---|
| $\rho$ | 0.854 | 0.841 | 0.819 |
| (s.e) | (0.053) | (0.133) | (0.060) |
| $\beta$ | 0.646 | 0.596 | 0.736 |
| (s.e) | (0.106) | (0.271) | (0.283) |
| implied $\lambda$ | 0.032 | 0.035 | 0.040 |
| (s.e.) | (0.013) | (0.032) | (0.015) |
| implied $\phi$ | 4.414 | 3.752 | 4.071 |
| (s.e.) | (1.942) | (4.302) | (1.958) |
| Sargan Stat | 33.13 | 19.01 | 29.39 |
| DOF | 33 | 14 | 28 |
| (p-value) | (0.46) | (0.16) | (0.39) |
| $m2$ | 0.848 | 0.859 | 0.850 |
| (p-value) | (0.20) | (0.20) | (0.20) |
| $N$ | 64 | 64 | 64 |
| $T$ | 5 | 5 | 5 |

All figures in parentheses are standard errors, unless otherwise specified.

The second regression, GMMb, was performed because simulations by Kiviet (1995) and Judson and Owen (1999) suggest that the smaller instrument set often results in lower bias for $\rho$ (at the cost of lower efficiency). In this case, the $\rho$ estimates for GMMa and GMMb are nearly identical, and therefore we prefer the GMMa results on efficiency grounds.

GMMc was performed primarily as a test of the assumption that, for all $s \leq t$, $E(\tilde{x}_{i,s} \ \widetilde{u}_{i,t}) = 0$. A Hausman test cannot reject the null hypothesis that $\theta_a = \theta_c$, where $\theta' = (\rho \quad \beta)$. We therefore conclude that the stronger predeterminacy assumptions embodied in GMMa are valid. Because all three estimators provide nearly identical estimates, the rest of our analysis will focus on the more efficient GMMa results.

Using the reduced form coefficients, we can recover the structural parameters of our model. Asymptotic standard errors are calculated using the delta method. The convergence coefficient, $\lambda$, and the elasticity of human capital, $\phi$ are significant at the 1% level and 2% level respectively.

We draw two primary conclusions from our results. First, the significance of $\lambda$ indicates that there is conditional convergence in productivity, confirming the catch-up hypotheses of Gerschenkron (1962) and others. Conditional on the level of human capital, countries with lower productivity will tend to see higher productivity growth. The speed of convergence is about 3% per year, which corresponds to a half-life of just under 24 years for deviations from the steady state.

Second, the level of human capital in a country exerts a strong influence on the dynamic path of TFP, by positively affecting the steady state growth path of productivity. Note that one does not need to subscribe to the model we set up in Section 3 to acknowledge the actual effect of human capital on productivity growth. Our model helps in interpreting the channel through which human capital exercises its influence; we argue that it does so by raising potential productivity temporarily above actual productivity. It is under this interpretation that $\phi$ measures the elasticity of potential productivity with respect to human capital. Our results support the Nelson-Phelps hypothesis that the level of human capital has a positive effect on a country's ability to take advantage of technological spillovers. Countries with higher levels of human capital converge to higher levels of productivity.

### 5.2 Dynamic and Static Effects of Human Capital

Our results imply that there is a useful distinction to be made between human capital's static effect and its dynamic effect. Our production function assumes that human capital directly impacts output in its role as an accumulable factor of production. An increase in human capital has an immediate level effect on income, whose magnitude is measured by the private Mincerian returns to education. This is the static effect.

An increase in human capital also increases the level of productivity along the long run growth path; our estimate for $\phi$ suggests that a one percent increase in a country's human capital leads to an increase in potential productivity of almost four and a half percent. Following an increase in human capital, productivity growth will be temporarily faster as productivity converges to the new, higher growth path. This is the dynamic effect.

Figures 1, 2 and 3 illustrate the process. All three figures are generated under the parameters estimated in GMMa. The hypothetical country shown is initially in its long run growth path of 2% per year (due to the exogeneously shifting world technology frontier). We examine the effect on the growth rate of $A$, $\log A$ and $\log y$ of an increase in human capital at time zero.

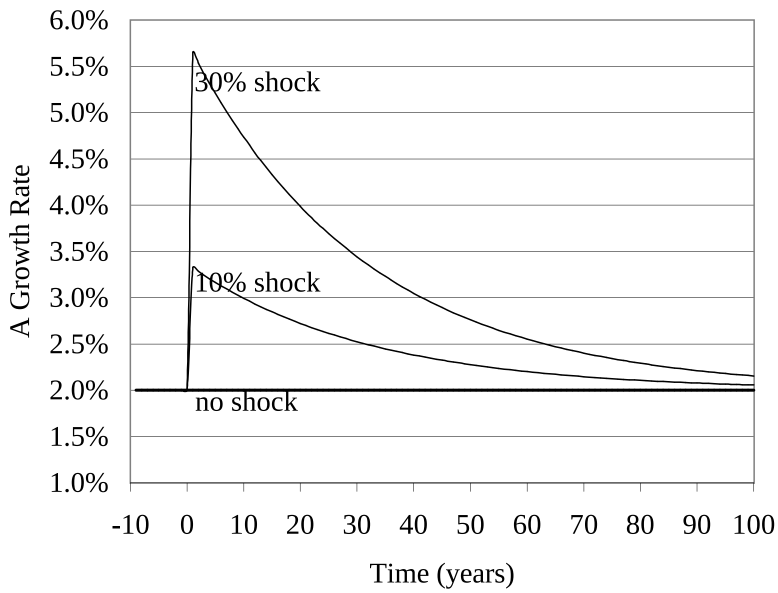
Figure 1 shows the response of the growth rate of $A$ to a 30% increase in human capital, a 10% increase, and no increase.[13] In the absence of change, $A$ grows at 2% per year. When there is a positive shock to human capital, the growth rate jumps up; the greater the shock, the higher the jump. Then it asymptotes back to 2% per year.

Figures 2 and 3 show the effect of shocks to human capital on $\log A$ and $\log y$. At time zero there is a discrete jump in $\log y$; this corresponds to the static effect that human capital has on output as a component of the production function. In subsequent periods the growth rate of $y$ (the slope of $\log y$) is raised above the long run level of 2%; the greater the increase in human capital, the higher the growth rates in subsequent periods. These growth rates asymptote back to the 2% base rate eventually, but the higher rates of growth persist for a considerable period.

The importance of transitional dynamics may be gauged by a cursory look at Figure 3. The static effect of a 30% shock to human capital is captured by the discrete vertical jump in log y at time zero. To see the magnitude of the dynamic effect, trace a line parallel to the no-shock line from $t = 0$ to $t = 100$ and examine the vertical distance between this line and the 30% shock-line. It is evident that over

[13] We have chosen arbitrary increases in human capital for illustrative purposes. An increase of 30% in a single period is quite improbable. The average yearly growth rate of h over a 5 year period is 3.6% with a standard deviation of 5%. South Korea has the highest increase, with a 92% gain over the whole 30 year sample period, which corresponds to an annual growth rate of 2.2%.

Figure 1: The Effect of Shocks to Human Capital on Productivity Growth




such a long period the dynamic effect of the increase in human capital is over three times as large as its static effect. In fact the two effects are about equal in as short a span as 10 years. Models that simply treat human capital as an accumulable factor in the production function while neglecting its dynamic role as a technology-enabler are therefore missing the most crucial link between education and output.

Figure 2: The Effect of Shocks to Human Capital on Productivity

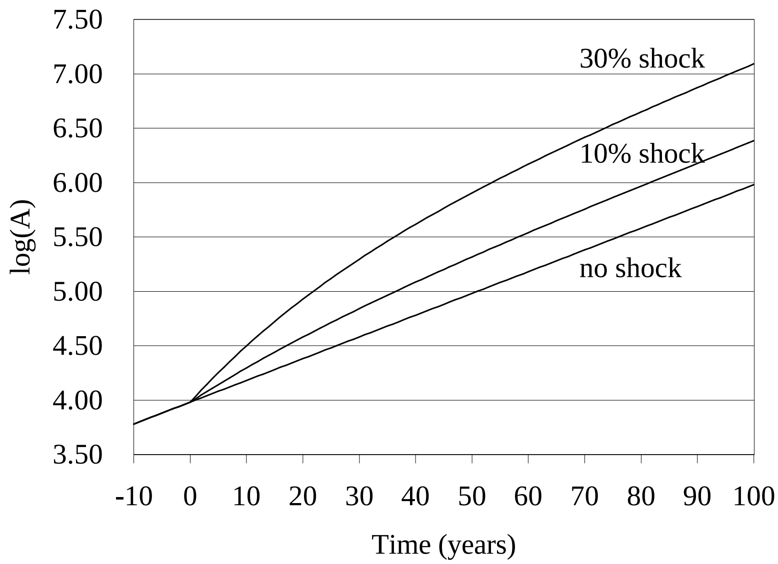
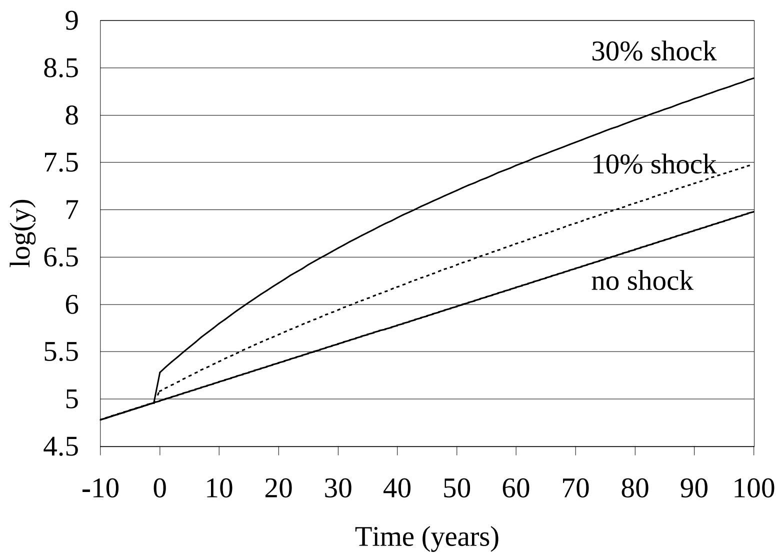



Figure 3: The Effect of Shocks to Human Capital on Output



### 5.3 Fixed Effects, Productivity and Human Capital

The methodology that we have used to examine the evolution of TFP across countries assumes that country-specific fixed effects are part of the story. It is therefore interesting to examine how much of the variation in long run TFP across nations is accounted for by human capital, and how much by the fixed factors in our formulation. Here we will show that our analysis is capable of offering some indicative answers.

Our fixed effects are recovered as follows:

$$\widehat{f}_i = \frac{1}{T}\sum_{t=1}^{T}(a_{i,t} - \widehat{\rho}a_{i,t-1} - \widehat{\beta}x_{i,t-1} - \widehat{\eta}_t) \tag{17}$$

Further, from equation (8), taking account of our panel notation, it is apparent that we may write:

$$\log A^*_{i,t} = \log F_i + \phi \log h_{i,t-1} + T_t \tag{18}$$

Letting a bar above variables denote deviations from the mean over countries at each point in time, it follows that:

$$\overline{\log A}^*_{i,t} = \overline{\log F}_i + \phi\overline{\log h}_{i,t-1} \tag{19}$$

From equation (19) it is possible to obtain a full set of estimates for the potential TFP of each country in each five year period (in deviations from country means) except for the earliest one.[14] This set of estimates can then be analyzed to determine what proportion of the variance in $\overline{\log A}^*_i$ can be attributed to each of the two components.

Table 4 contains the results of a variance decomposition, following the method described in Section 2.2. The two columns describe the proportion of the variance of

[14]The fact that potential TFP levels depend on lagged human capital implies that these levels may be recovered only for those periods for which we have lagged values of human capital available; this means that we cannot recover steady state levels for 1960.

Table 4: Variance Decomposition of Steady State Productivity

| | $\frac{cov(\overline{\log A_i^*}, \log Z)}{var(\overline{\log A_i^*})}$ | |
|---|---|---|
| Year | $Z = F_i$ | $Z = \phi h_{t-1}$ |
| 1965 | 0.134 | 0.866 |
| 1970 | 0.131 | 0.869 |
| 1975 | 0.064 | 0.936 |
| 1980 | 0.064 | 0.936 |
| 1985 | 0.043 | 0.957 |
| 1990 | 0.133 | 0.867 |

$\overline{\log A_i^*}$ which can be attributed to the fixed effects and human capital, respectively. The majority of the variance can be attributed to the human capital term. The decomposition is relatively stable over time, with human capital accounting for between 87% and 96% of the variation in $\overline{\log A_i^*}$.[15]

# 6 Alternative Samples and Specifications

We now turn to a discussion of additional results obtained through changes in our sample, methodology and specification. The following sections will compare our base results with results from a full sample including OECD countries, examine the importance of our correction for mining and quarrying, and consider an alternative measure of human capital as well as disaggregated measures of education. Our basic qualitative results are robust to these changes.

[15]Recall that an equivalent way of interpreting the variance decomposition is as a least-squares regression of, respectively, the fixed effects and lagged human capital on potential productivity. Thus, for example, had we in 1970 observed a (log) potential productivity level for some country that was 1 unit higher than the mean for all countries, then we would expect that country to have had 0.196 ($0.869/\phi$) years more of average education relative to the mean for all countries in 1965. All the regression coefficients for the human capital - productivity relationship are highly significant.

### 6.1 Full Sample

For our main results we focused only on non-OECD countries, assuming that our model was more appropriate for countries that were adopting technologies from the frontier, not creating new technologies. Table 5 reports the results for the full sample estimated using GMMa.

Table 5: Results for the Full Sample

| | Full Sample | non OECD |
|---|---|---|
| $\rho$ | 0.920 | 0.854 |
| (s.e) | (0.065) | (0.053) |
| $\beta$ | 0.712 | 0.646 |
| (s.e) | (0.102) | (0.106) |
| implied $\lambda$ | 0.017 | 0.032 |
| (s.e.) | (0.014) | (0.013) |
| implied $\phi$ | 8.861 | 4.414 |
| (s.e.) | (7.673) | (1.942) |
| Sargan Stat | 37.58 | 33.13 |
| DOF | 33 | 33 |
| (p-value) | (0.27) | (0.46) |
| $m2$ | 0.849 | 0.848 |
| (p-value) | (0.20) | (0.20) |
| $N$ | 86 | 64 |
| $T$ | 5 | 5 |

All figures in parentheses are standard errors, unless otherwise specified.

The reduced form results are quite similar for both samples. Interestingly, the standard errors of the non-OECD sample are nearly the same for $\beta$ and lower for $\phi$ even though the number of observations is lower by 22 countries. The recovered structural parameters are less similar, thought the confidence intervals still overlap. This is mainly due to the non-linear transformation needed to move from the reduced form to the structural parameters.

For the full sample, neither of the structural coefficients is significant. This suggests that our model of technology adoption is probably not appropriate for

OECD countries that engage in R&D themselves, and for whom internal efforts are comparable in importance to an exogenously determined technology frontier.

### 6.2 Mining Correction

Another potential issue is the effect that our corrections for mining have on our regressions. We noted earlier that countries with large resources of oil or minerals have implausibly high TFP in the absence of our correction. But for countries in which Mining and Quarrying is not exceptionally important, our correction should not make a substantive difference to our results.

We test this by omitting from our sample those countries for which Mining and Quarrying as a percentage of output exceeded 10% in any year. This reduces the number of countries to 41, and we run GMMa on this sample both with and without employing our adjustment procedure. As expected, the results are very similar (Table 6).

### 6.3 Human Capital Specification

Next we will look at how the results are altered by the specific formulation of human capital. Appendix A describes an alternative to the human capital specification that has been utilized to this point. Table 7 reports the results for our base method and this alternative method. The reduced form coefficients from both specifications fall within one another's confidence intervals. The structural parameters are more dissimilar, because of the non-linear transformation involved. All the qualitative results obtained thus far remain valid; all estimated parameters by either measure are highly significant.

### 6.4 Disaggregated Human Capital

In order to calculate TFP from our production function we needed an aggregate index of human capital. However, once we have obtained our TFP panel, we can

Table 6: Results With and Without Adjusting for Natural Resource-Extraction

| | Base Sample | min < 10% adjust | min < 10% no adjust |
|---|---|---|---|
| $\rho$ | 0.854 | 0.795 | 0.788 |
| (s.e) | (0.053) | (0.036) | (0.040) |
| $\beta$ | 0.646 | 0.772 | 0.798 |
| (s.e) | (0.106) | (0.081) | (0.087) |
| implied $\lambda$ | 0.032 | 0.050 | 0.048 |
| (s.e.) | (0.013) | (.009) | (0.010) |
| implied $\phi$ | 4.414 | 3.763 | 3.754 |
| (s.e.) | (1.942) | (0.803) | (0.814) |
| Sargan Stat | 33.13 | 36.28 | 35.17 |
| DOF | 33 | 33 | 33 |
| (p-value) | (0.46) | (0.32) | (0.37) |
| $m2$ | 0.848 | 0.915 | 0.964 |
| (p-value) | (0.20) | (0.18) | (0.17) |
| $N$ | 64 | 41 | 41 |
| $T$ | 5 | 5 | 5 |

All figures in parentheses are standard errors, unless otherwise specified.

examine the separate effects that primary, secondary and higher education have on steady-state levels of TFP. In terms of equation (14), instead of working with a single explanatory variable that is an aggregate index of human capital, we use three regressors: pyr (the average years of primary schooling in the population), syr (the average years of secondary education) and hyr (the average years of higher education). The corresponding coefficients are labeled $\beta_p$, $\beta_s$, and $\beta_h$ respectively. Note that we are no longer working from an explicit model as in all the other regressions. Consequently we cannot estimate any structural parameters. The results are reported in Table 8.

Again, all our estimates are strongly significant. It is interesting to observe that there is a progressively stronger impact of higher levels of education on TFP. This is despite the fact that the private returns to education incorporated in the production function follow a diminishing pattern. A possible reason for this result

Table 7: Results With an alternative human capital specification

| | Base Hum Cap | Alt Hum Cap |
|---|---|---|
| $\rho$ | 0.854 | 0.798 |
| (s.e) | (0.053) | (0.053) |
| $\beta$ | 0.646 | 0.561 |
| (s.e) | (0.106) | (0.097) |
| implied $\lambda$ | 0.032 | 0.045 |
| (s.e.) | (0.013) | (.013) |
| implied $\phi$ | 4.414 | 2.783 |
| (s.e.) | (1.942) | (0.945) |
| Sargan Stat | 33.13 | 35.77 |
| DOF | 33 | 33 |
| (p-value) | (0.46) | (0.34) |
| $m2$ | 0.848 | 0.840 |
| (p-value) | (0.20) | (0.20) |
| $N$ | 64 | 64 |
| $T$ | 5 | 5 |

All figures in parentheses are standard errors, unless otherwise specified.

Table 8: Results With Disaggregated Schooling

| | |
|---|---|
| $\rho$ | 0.765 |
| (s.e) | (0.025) |
| $\beta_{pyr}$ | 0.063 |
| (s.e) | (0.011) |
| $\beta_{syr}$ | 0.091 |
| (s.e) | (0.004) |
| $\beta_{hyr}$ | 0.169 |
| (s.e) | (0.030) |
| Sargan Stat | 78.62 |
| DOF | 71 |
| (p-value) | (0.26) |
| $m2$ | 0.778 |
| (p-value) | (0.436) |
| $N$ | 86 |
| $T$ | 5 |

All figures in parentheses are standard errors, unless otherwise specified.

is that, unlike private returns, later years of education may have a larger impact on the ability to implement new technologies.

# 7 Conclusion

We began this paper by retracing the debate about the relative importance of TFP and factor accumulation in the growth process. While Mankiw et al. (1992) contended that adding human capital to the factors of production explained most of the variation in per capita incomes across the world, subsequent papers found that differences in TFP were crucial. This paper has presented evidence that begins to reconcile these two conflicting points of view. While we find that TFP differences are important in accounting for variations in income, we also find that human capital plays a significant role in determining a country's *potential* TFP level. Our model and results show that conditional convergence in TFP is occurring, and that human capital plays a crucial role in determining the dynamic path of TFP. Both camps are therefore right: while productivity is the most important determinant of per capita income, the accumulation of human capital is the key to changes in productivity.

What is the channel whereby human capital affects productivity? We argue that international technology spillovers from countries at the frontier to developing countries are facilitated by human capital stocks. We do not doubt that other factors may also affect the ability of a country to implement new technologies. An appropriate direction for future research would appear to be to identify these other factors. Openness, the composition of a country's trade partners, the level of technology-enhancing FDI, macroeconomic stability and the prevalence of the rule of law are all promising candidates.

Finally, we believe that further research into the measurement of human capital is likely to be very beneficial to growth empirics. Our study demonstrates that human capital is perhaps the most crucial ingredient of the growth process, but it is based on necessarily broad and imprecise measures of human capital stocks. Moreover, although all the qualitative patterns that we have discussed are robust to changes in our index of human capital, we find that the magnitude of our point estimates (especially for structural parameters) is sensitive to such changes.

# A An Alternative Human Capital Specification

This section describes an alternative to the paper's standard method for calculating human capital stocks. Tables 9 and 10 below show two sets of Mincer coefficients reported by Psacharopoulos (1994). Table 9 shows different coefficients estimated by region, whereas Table 10 estimates different coefficients by income-level. Our base regressions (following Hall & Jones) work with selected figures from Table 9, while we work with Table 10.

Table 9: Mincerian Returns by Region

| Country | Years of Schooling | Coefficient (%) |
|---:|:---:|:---:|
| Sub-Saharan Africa | 5.9 | 13.4 |
| Asia | 8.4 | 9.6 |
| Eur/Mid East/N. Africa | 8.5 | 8.2 |
| Lat America/Caribbean | 7.9 | 12.4 |
| OECD | 10.9 | 6.8 |
| World | 8.4 | 10.1 |

Table 10: Mincerian Returns by Income-Level

| Country | Years of Schooling | Coefficient (%) |
|---:|:---:|:---:|
| Low Income ($610 or less) | 6.4 | 11.2 |
| Lower Middle Income (to $2449) | 8.4 | 11.7 |
| Upper Middle Income (to $7619) | 9.9 | 7.8 |
| High Income ($ 7620 or more) | 8.7 | 6.6 |

Our main specification picks the coefficients for Sub-Saharan Africa, the OECD and the World, and applies these to primary, secondary and higher education respectively for all countries in the sample. The alternative specification is taken from the second table, in which returns to education differ by income level and corresponding total years of schooling. We apply the first coefficient from Table 10 to total years of schooling under 6.4, the second coefficient to total years of schooling between 6.4 and

8.4, and so on. As an example, suppose that in the country of Narnia the average total years of schooling equal 10. The log of human capital per capita for Narnia is easily calculated as: $\log h = 6.4(0.112)+2(0.117)+1.5(0.078)+0.1(0.066) = 1.0744$.

Both methods of calculating human capital have their flaws. The base methodology involves arguing that the average rate of return to an additional year of schooling in Sub-Saharan Africa is the same as the rate of return to an additional year of primary schooling in any country. the alternative implies that the average rate of return to an additional year of schooling in the lowest income countries is the same as the rate of return to total years of schooling under 6.4 in all countries. The alternative method captures the fact that at very low levels of schooling, higher levels of schooling have a larger average return than lower levels of schooling (11.7% > 11.2%).

# B Data on the Share of Mining

From the United Nations publications referenced in the text of the paper, we compiled data on the share of Mining and Quarrying as a percentage of GDP for the years 1960, 1965, 1970, 1975, 1980, 1985 and 1990, for 139 countries for which appropriate national accounts data were available. Of these, we dropped all the countries for which suitable Barro-Lee education data were unavailable, or Summers-Heston data on GDP and capital per worker were unavailable. This left us with mining data on 88 countries, with missing data for some countries in some years.

Of these 88 countries, we designated 64 countries as “normal”. These are countries for which mining is not an especially important part of the economy, and for which the share of mining and quarrying was less than 5% for an overwhelming majority of years and countries. For most of these countries, moreover, data *was* available for every year. For those countries for which data was missing for three or less of our seven periods, we filled in the missing years by linear interpolation. For these countries, we also calculated the average share of mining across countries for each of the years in our sample, and an index with 1970=1 of the share of mining. The averages, from 1960 to 1990 are: 0.0146, 0.0133, 0.0189, 0.0136, 0.0153, 0.0164 and 0.0151. The corresponding index numbers are: 0.772, 0.707, 1, 0.813, 0.870 and 0.800.

We were left with eleven countries which we considered normal but still had data problems with, which we divided into two groups. The first group comprised Italy, Lesotho, the Central African Republic, Nicaragua and Portugal. For each of the countries in this group, we had data for three or more of the periods under consideration.In addition, each of these countries had data for 1970, the base year for our index of normal countries. For each of these countries, therefore, we filled in the missing years by multiplying the index for a given missing year by the share of mining in that country in 1970. The second group of countries comprised Iceland, Romania, Switzerland, Senegal, Mozambique and Swaziland. For these countries we had no data at all, and filled in every year according to the average mining share constructed for our normal countries.

We decided to group together the OPEC countries with Bahrain and Tunisia; our sub-sample here comprised Iran, Venezuela, Indonesia, Iraq, Kuwait, Algeria, Libya, and Tunisia. Of these countries, we had full data for the first four countries, and needed to construct one missing observation for Tunisia, and four for Algeria (Kuwait, Libya and Bahrain having to be subsequently dropped for lack of capital investment data). Since all countries had data for 1975, we constructed an index which reflected the average mining share by year for these countries, setting 1975=1. The index reads: 0.497, 0.585, 0.639, 1, 1.023, 0.662 and 0.570. We filled in the missing years for Tunisia and Algeria by multiplying the index for that year by the mining share in the relevant country in 1975.

This left us with 8 countries. For Niger, Papua New Guinea, Chile, Botswana and Togo we had data for four or more of the periods under consideration, and filled in the remainder using linear interpolation. Zaire and the USSR were regretfully dropped.

## C GMM Estimation

We can rewrite equation (14) as

$$Y_{i,t} = X_{i,t}\ \theta + v_{i,t} \tag{20}$$

where $\theta' = (\rho\ \beta),\ \ v_{i,t} = \Delta\tilde{u}_{i,t}$

$$Y_i = \begin{bmatrix} \Delta\tilde{a}_{i,3} \\ \vdots \\ \Delta\tilde{a}_{i,T} \end{bmatrix}, \quad X_i = \begin{bmatrix} \Delta\tilde{a}_{i,2} & \Delta\tilde{x}_{i,2} \\ \vdots & \vdots \\ \Delta\tilde{a}_{i,T-1} & \Delta\tilde{x}_{i,T-1} \end{bmatrix} \tag{21}$$

$$Y' = \{Y_1', \ldots, Y_N'\}, \quad X' = \{X_1', \ldots, X_N'\}$$

using the notation $\Delta\tilde{a}_{i,t} = \tilde{a}_{i,t} - \tilde{a}_{i,t-1}$ for differenced variables.

The GMM orthogonality conditions can be expressed in terms of the differenced error terms:

$$E(\tilde{a}_{i,s}\ v_{i,t}) = 0, \quad s \leq t-2 \tag{22}$$

$$E(\tilde{x}_{i,s}\ v_{i,t}) = 0, \quad s \leq t-1 \tag{23}$$

For $t = 3$, the first period for which all lags are available, these orthogonality conditions indicate that $a_{i,1}, x_{i,1}$ and $x_{i,2}$ are valid instruments. In each successive time period one additional $x$ and one additional $y$ value become valid instruments.

The complete instrument set takes on the form

$$Z_i^a = \begin{bmatrix} \tilde{a}_{i,1} \quad \tilde{x}_{i,1} \quad \tilde{x}_{i,2} & & & 0 \\ & \tilde{a}_{i,1} \quad \tilde{a}_{i,2} \quad \tilde{x}_{i,1} \cdots \tilde{x}_{i,3} & & \\ & & \ddots & \\ 0 & & & \tilde{a}_{i,1} \cdots \tilde{a}_{i,5} \quad \tilde{x}_{i,1} \cdots \tilde{x}_{i,6} \end{bmatrix} \tag{24}$$

$$Z' = \{Z_1', \ldots, Z_N'\}$$

This instrument set corresponds to the regressions labeled GMMa in the text. In addition, regressions were performed using two different subsets of these instruments.

$$Z_i^b = \begin{bmatrix} \tilde{a}_{i,1} & & & 0 & \Delta\tilde{x}_{i,2} \\ & \tilde{a}_{i,1} \quad \tilde{a}_{i,2} & & & \Delta\tilde{x}_{i,3} \\ & & \ddots & & \vdots \\ 0 & & & \tilde{a}_{i,1} \cdots \tilde{a}_{i,5} & \Delta\tilde{x}_{i,6} \end{bmatrix} \tag{25}$$

$$Z_i^c = \begin{bmatrix} \tilde{a}_{i,1} \quad \tilde{x}_{i,1} & & & 0 \\ & \tilde{a}_{i,1} \quad \tilde{a}_{i,2} \quad \tilde{x}_{i,1} \quad \tilde{x}_{i,2} & & \\ & & \ddots & \\ 0 & & & \tilde{a}_{i,1} \cdots \tilde{a}_{i,5} \quad \tilde{x}_{i,1} \cdots \tilde{x}_{i,5} \end{bmatrix} \tag{26}$$

Given any of the instrument sets, the GMM orthogonality conditions can be expressed as $E(Z_i' v_i(\theta)) = 0$. The GMM estimator for $\theta$ is

$$\hat{\theta}_j = (X'ZA_jZ'X)^{-1}X'ZA_jZ'Y \tag{27}$$

where $A_j$ is any positive semidefinite matrix. The optimal weight matrix is $A_j^* = E(Z_i' v_i v_i' Z_i)$. An estimate for the optimal weight matrix can be found using a two stage process. A first stage estimate is found using

$$A_1 = \left( \frac{1}{N} \sum_{i=1}^{N} Z_i' H Z_i \right)^{-1} \tag{28}$$

where H is a (T-2)x(T-2) matrix with twos on the diagonal, negative ones on the first off diagonal, and zeros otherwise. Using $A_1$, a first stage estimate for $\theta$, $\hat{\theta}_1$ can be found using (27). The first stage estimated errors, $\hat{v^1} = Y - X\hat{\theta}_1$ can be used to calculate a second stage weight matrix,

$$A_2 = \left( \frac{1}{N} \sum_{i=1}^{N} Z_i' \hat{v^1}_i \hat{v^1}_i' Z_i \right)^{-1} \tag{29}$$

which can be used to find $\hat{\theta}_2$. The asymptotic variance covariance matrix can be estimated by

$$V_j = N(X'ZA_jZ'X)^{-1} X'ZA_j \left( \sum_{i=1}^{N} Z_i' \hat{v}_i \hat{v}_i' Z_i \right) A_j Z'X(X'ZA_jZ'X)^{-1} \tag{30}$$

which simplifies in the second stage to

$$V_2 = N(X'ZA_2Z'X)^{-1} \tag{31}$$

# D TFP as a ratio to $A_{USA,1960}$

| CODE | Name | 1960 | 1965 | 1970 | 1975 | 1980 | 1985 | 1990 | OECD | Mining |
|---|---|---|---|---|---|---|---|---|---|---|
| ARG | Argentina | 0.87 | 0.93 | 0.96 | 1.00 | 0.99 | 0.75 | 0.58 | | |
| AUS | Australia | 0.72 | 0.79 | 0.86 | 0.86 | 0.85 | 0.90 | 0.95 | oecd | |
| AUT | Austria | 0.86 | 0.98 | 1.01 | 1.07 | 1.08 | 1.04 | 1.15 | oecd | |
| BEL | Belgium | 0.64 | 0.79 | 0.94 | 1.04 | 1.14 | 1.09 | 1.30 | oecd | |
| BGD | Bangladesh | 0.55 | 0.71 | 0.85 | 0.63 | 0.79 | 0.90 | 1.06 | | |
| BOL | Bolivia | 0.18 | 0.24 | 0.34 | 0.35 | 0.35 | 0.34 | 0.38 | | mining |
| BRA | Brazil | 0.52 | 0.52 | 0.70 | 0.98 | 1.05 | 0.88 | 0.78 | | |
| BRB | Barbados | 0.56 | 0.71 | 0.78 | 0.75 | 0.93 | 0.70 | 0.86 | | |
| BWA | Botswana | 0.18 | 0.21 | 0.30 | 0.34 | 0.38 | 0.28 | 0.28 | | mining |
| CAF | Central African Republic | 0.19 | 0.17 | 0.21 | 0.20 | 0.23 | 0.21 | 0.20 | | |
| CAN | Canada | 0.79 | 0.98 | 1.03 | 1.07 | 1.02 | 1.10 | 1.17 | oecd | |
| CHE | Switzerland | 1.02 | 1.12 | 1.29 | 1.13 | 1.01 | 1.01 | 1.10 | oecd | |
| CHL | Chile | 0.51 | 0.60 | 0.62 | 0.43 | 0.62 | 0.47 | 0.56 | | mining |
| CMR | Cameroon | 0.27 | 0.29 | 0.35 | 0.36 | 0.43 | 0.49 | 0.25 | | mining |
| COL | Colombia | 0.45 | 0.53 | 0.68 | 0.67 | 0.80 | 0.69 | 0.69 | | |
| CRI | Costa Rica | 0.67 | 0.81 | 0.96 | 0.87 | 0.85 | 0.63 | 0.66 | | |
| CYP | Cyprus | 0.24 | 0.34 | 0.49 | 0.29 | 0.57 | 0.62 | 0.84 | | |
| DEU | Germany | 0.61 | 0.72 | 0.85 | 0.87 | 1.01 | 0.99 | 1.13 | oecd | |
| DNK | Denmark | 0.62 | 0.72 | 0.75 | 0.68 | 0.71 | 0.82 | 0.81 | oecd | |
| DOM | Dominican Republic | 0.47 | 0.55 | 0.67 | 0.74 | 0.75 | 0.56 | 0.49 | | |
| DZA | Algeria | 0.70 | 0.66 | 0.93 | 0.83 | 0.78 | 0.88 | 0.72 | | mining |
| ECU | Ecuador | 0.35 | 0.40 | 0.46 | 0.57 | 0.57 | 0.42 | 0.41 | | mining |
| ESP | Spain | 0.62 | 0.98 | 1.07 | 1.29 | 1.13 | 1.07 | 1.30 | oecd | |
| FIN | Finland | 0.46 | 0.54 | 0.62 | 0.67 | 0.70 | 0.76 | 0.87 | oecd | |
| FRA | France | 0.87 | 1.07 | 1.29 | 1.26 | 1.30 | 1.22 | 1.34 | oecd | |
| GBR | United Kingdom | 0.81 | 0.92 | 0.93 | 0.91 | 0.89 | 0.96 | 1.18 | oecd | |
| GHA | Ghana | 0.35 | 0.33 | 0.39 | 0.33 | 0.39 | 0.33 | 0.29 | | |
| GRC | Greece | 0.41 | 0.56 | 0.71 | 0.74 | 0.75 | 0.75 | 0.78 | oecd | |
| GTM | Guatemala | 0.79 | 0.90 | 1.04 | 1.14 | 1.16 | 0.85 | 0.90 | | |
| GUY | Guyana | 0.34 | 0.28 | 0.29 | 0.43 | 0.25 | 0.15 | 0.11 | | mining |
| HKG | Hong Kong, China | 0.28 | 0.49 | 0.64 | 0.68 | 0.94 | 0.93 | 1.24 | | |
| HND | Honduras | 0.38 | 0.45 | 0.48 | 0.46 | 0.54 | 0.41 | 0.39 | | |
| HTI | Haiti | 0.54 | 0.52 | 0.47 | 0.43 | 0.47 | 0.31 | 0.28 | | |
| IDN | Indonesia | 0.27 | 0.25 | 0.26 | 0.25 | 0.26 | 0.30 | 0.30 | | mining |
| IND | India | 0.26 | 0.24 | 0.24 | 0.22 | 0.23 | 0.26 | 0.30 | | |
| IRL | Ireland | 0.45 | 0.56 | 0.70 | 0.76 | 0.80 | 0.77 | 1.02 | oecd | |
| IRN | Iran, Islamic Rep. | 1.42 | 1.64 | 2.14 | 1.50 | 0.88 | 1.04 | 0.75 | | mining |
| ISL | Iceland | 0.66 | 0.80 | 0.73 | 0.83 | 1.01 | 0.96 | 1.00 | oecd | |
| ISR | Israel | 0.46 | 0.64 | 0.78 | 0.90 | 0.83 | 0.86 | 0.98 | | |
| ITA | Italy | 0.66 | 0.78 | 1.06 | 1.09 | 1.44 | 1.35 | 1.50 | oecd | |
| JAM | Jamaica | 0.28 | 0.36 | 0.41 | 0.42 | 0.26 | 0.26 | 0.29 | | mining |
| JOR | Jordan | 0.89 | 1.15 | 0.73 | 0.93 | 1.71 | 1.27 | 0.80 | | |
| JPN | Japan | 0.31 | 0.40 | 0.63 | 0.58 | 0.62 | 0.69 | 0.79 | oecd | |
| KEN | Kenya | 0.13 | 0.13 | 0.12 | 0.21 | 0.22 | 0.20 | 0.19 | | |
| KOR | Korea, Rep. | 0.32 | 0.31 | 0.44 | 0.46 | 0.44 | 0.49 | 0.71 | | |

| CODE | Name | 1960 | 1965 | 1970 | 1975 | 1980 | 1985 | 1990 | OECD | Mining |
|---|---|---|---|---|---|---|---|---|---|---|
| LKA | Sri Lanka | 0.54 | 0.47 | 0.46 | 0.44 | 0.45 | 0.51 | 0.46 | | |
| LSO | Lesotho | 0.10 | 0.15 | 0.13 | 0.25 | 0.24 | 0.21 | 0.19 | | |
| MEX | Mexico | 1.05 | 1.27 | 1.34 | 1.49 | 1.57 | 1.18 | 1.06 | | |
| MLI | Mali | 0.31 | 0.24 | 0.23 | 0.27 | 0.30 | 0.33 | 0.20 | | |
| MLT | Malta | 0.25 | 0.26 | 0.41 | 0.51 | 0.79 | 0.81 | 0.98 | | |
| MOZ | Mozambique | 0.74 | 0.84 | 0.99 | 0.63 | 0.47 | 0.40 | 0.47 | | |
| MUS | Mauritius | 0.72 | 0.73 | 0.47 | 0.76 | 0.66 | 0.68 | 0.95 | | |
| MWI | Malawi | 0.15 | 0.16 | 0.15 | 0.15 | 0.14 | 0.14 | 0.16 | | |
| MYS | Malaysia | 0.44 | 0.46 | 0.60 | 0.58 | 0.65 | 0.54 | 0.65 | | mining |
| NER | Niger | 0.17 | 0.21 | 0.27 | 0.16 | 0.18 | 0.15 | 0.15 | | mining |
| NIC | Nicaragua | 0.68 | 1.08 | 0.96 | 0.97 | 0.62 | 0.55 | 0.33 | | |
| NLD | Netherlands | 1.01 | 1.17 | 1.15 | 1.11 | 1.11 | 1.02 | 1.22 | oecd | |
| NOR | Norway | 0.67 | 0.84 | 0.85 | 0.89 | 0.82 | 0.86 | 0.89 | oecd | mining |
| NZL | New Zealand | 0.83 | 0.94 | 0.92 | 0.87 | 0.74 | 0.79 | 0.78 | oecd | |
| PAK | Pakistan | 0.38 | 0.49 | 0.52 | 0.44 | 0.55 | 0.62 | 0.62 | | |
| PAN | Panama | 0.39 | 0.51 | 0.60 | 0.56 | 0.60 | 0.58 | 0.39 | | |
| PER | Peru | 0.45 | 0.66 | 0.67 | 0.82 | 0.50 | 0.39 | 0.32 | | mining |
| PHL | Philippines | 0.31 | 0.33 | 0.21 | 0.35 | 0.34 | 0.23 | 0.28 | | mining |
| PNG | Papua New Guinea | 0.28 | 0.47 | 0.51 | 0.36 | 0.34 | 0.30 | 0.23 | | mining |
| PRT | Portugal | 0.50 | 0.60 | 0.77 | 0.85 | 0.49 | 0.77 | 1.28 | oecd | mining |
| PRY | Paraguay | 0.49 | 0.54 | 0.52 | 0.56 | 0.78 | 0.47 | 0.47 | | |
| ROM | Romania | 0.04 | 0.06 | 0.09 | 0.12 | 0.12 | 0.18 | 0.15 | | |
| SEN | Senegal | 0.39 | 0.45 | 0.45 | 0.39 | 0.40 | 0.48 | 0.45 | | |
| SGP | Singapore | 0.40 | 0.45 | 0.72 | 0.90 | 1.08 | 1.02 | 1.33 | | |
| SLV | El Salvador | 0.76 | 0.91 | 0.84 | 0.89 | 0.69 | 0.61 | 0.60 | | |
| SWE | Sweden | 0.80 | 0.96 | 1.05 | 1.00 | 0.92 | 1.00 | 1.07 | oecd | |
| SWZ | Swaziland | 0.30 | 0.45 | 0.71 | 0.66 | 0.78 | 0.47 | 0.56 | | mining |
| SYR | Syrian Arab Republic | 0.72 | 0.99 | 1.12 | 1.77 | 1.71 | 1.37 | 0.99 | | mining |
| TGO | Togo | 0.12 | 0.18 | 0.22 | 0.17 | 0.15 | 0.13 | 0.14 | | mining |
| THA | Thailand | 0.22 | 0.26 | 0.31 | 0.30 | 0.38 | 0.36 | 0.52 | | |
| TTO | Trinidad and Tobago | 0.99 | 1.26 | 1.69 | 1.09 | 1.11 | 1.14 | 0.81 | | mining |
| TUN | Tunisia | 0.50 | 0.58 | 0.64 | 0.81 | 0.84 | 0.81 | 0.86 | | mining |
| TUR | Turkey | 0.35 | 0.40 | 0.51 | 0.66 | 0.55 | 0.55 | 0.67 | | |
| UGA | Uganda | 0.33 | 0.34 | 0.36 | 0.34 | 0.29 | 0.30 | 0.31 | | |
| URY | Uruguay | 0.72 | 0.69 | 0.81 | 0.79 | 0.87 | 0.52 | 0.65 | | |
| USA | United States | 1.00 | 1.16 | 1.18 | 1.10 | 1.00 | 1.10 | 1.19 | oecd | |
| VEN | Venezuela | 1.05 | 1.50 | 1.85 | 1.26 | 0.90 | 0.85 | 0.72 | | mining |
| YUG | Yugoslavia, FR | 0.22 | 0.29 | 0.41 | 0.53 | 0.60 | 0.46 | 0.35 | | |
| ZAF | South Africa | 0.39 | 0.50 | 0.59 | 0.64 | 0.53 | 0.50 | 0.54 | | mining |
| ZMB | Zambia | 0.07 | 0.11 | 0.12 | 0.21 | 0.13 | 0.10 | 0.10 | | mining |
| ZWE | Zimbabwe | 0.15 | 0.16 | 0.20 | 0.28 | 0.24 | 0.30 | 0.23 | | |

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