A Contribution to the Empirics of Total Factor Productivity

Shekhar Aiyar & James Feyrer

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Introduction

Much recent work in the growth literature has emphasized the importance of total factor productivity as opposed to factor accumulation in the process of economic growth. The issue is central not just to gaining an intellectual understanding of economic growth, but also in terms of policy implications for poor countries that wish to close the gap between themselves and the rich world as rapidly as possible. Policies that emphasize factor accumulation may differ from those that emphasize the need to advance to the world technology frontier.

In some ways, the genesis of the debate may be traced to a paper by Mankiw, Romer & Weil (1992). Their work 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 the majority of differences in income per capita under the assumption that all countries shared a common level of productivity.

This assumption turned turned out to be unwarranted. Their findings have been disputed by a series of panel studies such as Knight, Loyaza & Villanueva (1993), Islam (1995) and Caselli, Esquivel & Lefort (1996), which demonstrate that while convergence is indeed taking place, the convergence is conditional on differing levels of productivity across countries.

These studies imply that it is of primary importance to understand the factors that determine a country's steady state and move it upward over the course of time, for *given* the steady state, convergence toward it appears to be very rapid (give figures?). Moreover, 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. It is found that differences in technology are pervasive and important in determining steady states. Therefore an analysis of why countries differ so much in their technologies, of how differences in technology between countries have evolved, and of the factors governing this evolution, would seem essential. Unfortunately, panel studies of the kind carried out by Islam and CEL cannot, by their nature, cannot show the evolution of differences in technology, since only a single fixed effect is recovered for each country.

These panels studies have focused greater attention on productivity. Several recent papers have concentrated on calculating total factor productivity (TFP) for a large sample of countries at a single point in time [1]. TFP is calculated as a (Solow) residual from real income per capita, after accounting for the contribution of various factors of production. Klenow & Rodgriguez-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. Their results are corroborated by Hall & 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.

This paper starts with the premise that differences in TFP indeed play a central role in the growth process, and that it is therefore both interesting and important to analyze how differences in TFP between countries have evolved over time, and what factors have governed this evolution.

There are several hypotheses in the literature concerning the process of technological growth in a single country. Grossman & Helpman (1991) and Aghion & Howitt (1992) describe economies in which purposive research and development is the engine that drives technical progress, modeled either as an ever-increasing variety of products or as a series of quality improvements to existing products. However, most research and development is overwhelmingly concentrated in a handful of rich countries [2], 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 a series of models (references?) that emphasize the ability of "follower" countries to imitate the innovations carried out in "leader" countries, an idea with a long lineage including Gerschenkron (1962). Various factors may be thought to influence the efficacy with which such imitation can 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 fron-

[1] TFP is more or less synonymous with technology broadly defined, since both are a measure of the efficiency with which a country combines its factors of production to obtain goods and services. The terms are used interchangeably in this paper.

[2] need to cite numbers

tier), 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 hypothesis that the stock of human capital in a follower country is a crucial determinant of the extent to which it will be able to imitate innovations carried out at the frontier has a long pedigree, dating back to Nelson & Phelps (1966). More recently several empirical papers, such as Benhabib & 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 through the lens of its direct effect as an accumulable factor in the production function. Klenow & Bils (2000) claim that 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 & 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 contribute to the empirics of TFP by calculating Solow residuals for a large panel of countries over a thirty year period, and then examining the evolution of these residuals for our sample. We pay particular attention to the issue of whether TFP is converging, and whether human capital stocks are indeed a significant determinant of the different steady state TFP levels toward which different countries are 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 a point in time, and its potential (or steady-state) TFP level. The latter is a function of three things: the country's stock of human capital per worker, the level of TFP that obtains at the world technological frontier, and an index of fixed and unobservable factors peculiar to the country in question. From this hypothesis we derive an empirical specification that consists of a fixed-effects dynamic panel regression, which we proceed to run using our panel of TFP figures. To preview our results, we find that conditional convergence does indeed obtain at about 3% per year. Human capital stocks are positive and significant in determining a country's target TFP level; our estimates of the elasticity of potential TFP with respect to human capital per worker, which vary according to our choice of econometric technique, are uniformly large and positive.

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. The third section lays out the theoretical framework from which our empirical specification is derived, explaining which hypotheses in the literature may be tested using our approach, and, perhaps equally importantly, which may not. The fourth section describes our results and also briefly reviews the properties of the three different estimators that we employ. The fifth section embarks on a tentative analysis of the country-specific fixed effects that we are able to recover, and discusses the relative importance of fixed factors versus human capital stocks in determining a country's steady state level of TFP. The sixth section concludes with some suggested directions for future research.

1 Calculating Total Factor Productivity

Our methodology for calculating TFP has much in common with recent work by Klenow & Rodgriguez-Clare (1997) (KRC) and Hall & Jones (1999) (HJ). We postulate that the aggregate production function takes a simple Cobb-Douglas form and then calculate TFP as a Solow residual.

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

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 output. 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.

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

$$y_i = A_i k_i^{\frac{\alpha}{1-\alpha}} h_i \tag{3}$$

This is exactly the formulation used by Hall & Jones (1999), and 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. We differ from them, however, in the way that we calculate h_i.

Table 1A and 1B below show two sets of Mincer coefficients reported by Psacharopoulos (1994). Table 1A shows different coefficients for primary, secondary and higher education for different regions of the world, while Table 1B shows a single Mincerian coefficient for four different sets of countries, grouped not by region but by per capita income. Essentially Hall and Jones work with selected figures from Table 1A while we work with Table 1B.

INSERT TABLES

Discussion of why we've used our method, but how close it is to H&J. Say we get educ figures from barlee. The correlation between countries of human capital as measured by us and as measured by Hall and Jones is well above 0.99 for every year in the sample. Moreover, using the HJ methodology leaves the econometric estimates of Section 4 qualititatively unchanged and quantitatively within a 5% range of the point estimates that we obtain (NOTE: I used Anderson-Hsiao on all countries from 1960-90 to establish this).

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 & Levine (2000) (check ref) [3]. All figures are in PPP adjusted international dollars.

Before calculating TFP, we make an adjustment to correct for the use of natural resources: we subtract from GDP the share of it that is attributable to Mining and Quarrying in national income accounts, using data from a series of UN publications[4]. In order to carry out this exercise 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 1 [5].

One point that should be made here is that our correction procedure may be flawed in the sense that it penalizes resource rich countries *too* heavily. Ideally we would like data on the shares of labor, physical capital and human capital that are employed in Mining and Quarrying, so that we can subtract them from their respective factors in the production function before calculating the Solow residual. Unfortunately, data of this kind are unavailable for our panel. To the extent that an oil rich country uses a

[3] Their calculations, in turn, are based on the Penn World Tables 5.6. Both are available from the World Bank website (http://www.wordbank.org/research/growth)

[4] give the references.

[5] The central hypotheses that we test in this paper are not very sensitive to this correction procedure; our qualitative results for convergence and the elasticity of steady state TFP with respect to human capital hold for the uncorrected data as well (check this!). But we deem the correction necessary on both theoretical and empirical grounds - without making the correction oil and mineral rich countries are found to have implausibly high TFP levels.

greater share of (say) its physical capital in the mining sector than an oil poor country, we will underestimate TFP in the former. Nonetheless, it seems preferable to make the correction than not, for we would surmise that for resource rich countries, the share of output attributable to the mining sector is far greater than the share of factors of production employed there, due to the essentially extractive nature of the sector.

Finally, we assume that $\alpha = 1/3$, as is standard in the literature. 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 below shows the log of TFP for some representative countries for the years 1960, 1975 and 1990 (see Appendix 3 for our complete panel of figures).

	log Ai		
Country	1960 (Rank)	1975 (Rank)	1990 (Rank)
Romania	5.597 (86)	6.630(86)	6.834(83)
Kenya	6.656 (82)	7.164(81)	7.123(77)
India	7.377 (72)	7.256(79)	7.580(67)
Hong Kong	7.512 (66)	8.392(42)	8.937(7)
Japan	7.575 (63)	8.203(53)	8.472(37)
Singapore	7.857 (50)	8.685(21)	9.062(2)
Brazil	8.106 (37)	8.744(17)	8.536(33)
Colombia	7.974 (47)	8.395(41)	8.425(41)
Germany	8.260 (31)	8.588(26)	8.835(13)
Canada	8.501 (15)	8.775(15)	8.863(12)
U.K.	8.536 (12)	8.644(25)	8.886(10)
U.S.A.	8.719 (7)	8.797(13)	8.886(11)
World Average	7.905	8.226	8.169
OECD Average	8.352	8.662	8.792

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

Clearly, the table throws up a few surprises. The average rate of growth of TFP over the period as a whole for the full sample is 1.1% a year. But average productivity actually seems to be lower in 1990 than in 1975 (although TFP rises between 1975 and 1980, falling only thereafter). This pattern, however, is not true for rich countries; for the OECD countries in our sample average productivity grew steadily in every five year period except between 1975 and 1980, when it fell by a little under 2%. In the USA productivity fell over both periods in the 1970s, but rose in all other periods (note that the 1970s correspond to the American "productivity slowdown" as measured using far more comprehensive disaggregated data (references?)).

The lowest TFP in the world 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 about 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 4.9% per annum over the period, while Singapore moved up 42 places with a 4% per annum growth rate. At the other end of the spectrum, Guyana registered negative growth at an average of 2.2% per annum, while Nicaragua, Iran and Haiti registered negative growth of over 1% per annum.

As far as "sigma-convergence" goes Barro & Sala-i-Martin (1995), it is hard to discern a clear-cut trend. The progression of the standard deviation of $\log A_i$ from 1960 to 1990 reads: 0.6591, 0.6596, 0.6487, 0.6038, 0.6110, 0.6165, 0.6732. That is, the dispersion of the countries narrows between 1960 and 1975, and rises steadily thereafter, to end the period a shade wider than it was at the outset.

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.

Define $X_i = (\frac{K_i}{Y_i})^{\frac{\alpha}{1-\alpha}} h_i$. Then $\log y_i = \log A_i + \log X_i$, and

$$\frac{var(\log y_i)}{var(\log y_i)} = \frac{cov(\log y_i, \log A_i)}{var(\log y_i)} + \frac{cov(\log y_i, \log X_i)}{var(\log y_i)} = 1 \qquad (4)$$

This "split" gives us an idea of how much of the 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 KRC 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 below shows the results of this decomposition by year.

It is apparent that the decomposition has remained rather stable over the years, ranging from a 59% - 41% split between TFP and factors of production in 1960 to a 55% - 45% split in 1975 at the extremes. Our premise that differences in TFP are at least as important as differences in factors of production thus finds overwhelming support in every year of our sample. Accordingly, the next section develops our hypotheses about the evolution of TFP and derives the empirical specification that we use in estimation.

Year	$\frac{cov(\log y_i, \frac{\alpha}{1-\alpha}\log k_i)}{var(\log y_i)}$	$\frac{cov(\log y_i, \log h_i)}{var(\log y_i)}$	$\frac{cov(\log y_i, \log X_i)}{var(\log y_i)}$	$\frac{cov(\log y_i, \log A_i)}{var(\log y_i)}$
1960	.1859	.2207	.4066	.5935
1965	.1901	.2187	.4088	.5910
1970	.1896	.2336	.4232	.5767
1975	.2060	.2423	.4483	.5517
1980	.1895	.2569	.4464	.5536
1985	.1836	.2540	.4375	.5624
1990	.1704	.2459	.4163	.5837

Table 2: Variance Decomposition of Log Incomes by Year

2 The Model

We start with a working hypothesis in the spirit of Nelson & 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.

$$\frac{\dot{A}}{A}(t) = \lambda(\log A^*(t) - \log A(t)) \quad (5)$$

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

$$A^*(t) = Fh^{\phi}T(t) \quad (6)$$

where F is an index of fixed factors specific to the country, and $T(t)$ represents the TFP level at the world technological frontier.

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

Noting that $\frac{\dot{A}}{A}$ is the time derivative of $\log A$, multiplying equation (5) through by $e^{\lambda t}$ and rearranging terms allows us to obtain:

$$e^{\lambda t}(\log \dot{A}(t) + \lambda \log A(t)) = e^{\lambda t}\lambda(\log F + \phi \log h + \log T(t)) \quad (7)$$

It follows that:

$$\int_{t_1}^{t_2} e^{\lambda t}(\log \dot{A}(t) + \lambda \log A(t))dt = \log F \int_{t_1}^{t_2} \lambda e^{\lambda t}dt + \phi \log h \int_{t_1}^{t_2} \lambda e^{\lambda t}dt + \int_{t_1}^{t_2} e^{\lambda t} \log T(t)dt \quad (8)$$

Finally, performing the integration in (8), multiplying through by $e^{-\lambda t_2}$ and rearranging terms yields:

$$\log A(t_2) = e^{-\lambda\tau}\log A(t_1) + \phi(1-e^{-\lambda\tau})\log h + (1-e^{-\lambda\tau})\log F \\ + e^{-\lambda t_2}\int_{t_1}^{t_2} e^{\lambda t}\log T(t)dt \tag{9}$$

where $\tau = (t_2 - t_1)$. Equation (9) falls neatly into the class of dynamic panel models with a fixed effect and a time trend. To see this, define:

$$\begin{aligned} y_{i,t} &= \log A(t_2) \\ y_{i,t-1} &= \log A(t_1) \\ x_{i,t-1} &= \log h \\ f_i &= (1-e^{-\lambda\tau})\log F \\ \beta &= \phi(1-e^{-\lambda\tau}) \\ \rho &= e^{-\lambda\tau} \\ \eta_t &= e^{-\lambda t_2}\int_{t_1}^{t_2} e^{\lambda t}\log T(t)dt \end{aligned} \tag{10}$$

Then, with the addition of a disturbance term, we can write (9) as:

$$y_{i,t} = f_i + \rho y_{i,t-1} + \beta x_{i,t-1} + \eta_t + u_{i,t} \tag{11}$$

where f_i is a country specific fixed effect, η_t is a time trend that is common to all countries, and $u_{i,t}$ is the random error term. It is apparent that λ and ϕ are easily recovered from the coefficients ρ and β respectively. We use equation (11) 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 & 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 [6]. Were this data available for our panel, we could have added an index of the R&D

[6] Although Coe and Helpman 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) (need reference) for a rebuttal of the latter claim.

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.

3 Model Estimation

In the previous section we derived a regression specification of the form [7]

$$y_{i,t} = f_i + \rho y_{i,t} + \beta x_{i,t} + \eta_t + u_{i,t}, \quad i = 1 \ldots N, \quad t = 2 \ldots T \tag{12}$$

We will estimate (12) using an application of the generalized method of moments estimator (GMM) for dynamic panels suggested by Arellano & Bond (1991) and familiar to the empirical growth literature through Caselli, Esquivel & Lefort (1996). As noted in depth by CEL, GMM estimation is appropriate in this context because it is capable of producing 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 (12) 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.

$$\tilde{y}_{i,t} - \tilde{y}_{i,t-1} = \rho(\tilde{y}_{i,t-1} - \tilde{y}_{i,t-2}) + \beta(\tilde{x}_{i,t-1} - \tilde{x}_{i,t-2}) + (\tilde{u}_{i,t} - \tilde{u}_{i,t-1}) \tag{13}$$

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

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

[7]T is measured as the number of time periods for which $y_{i,t}$ observations exist. The index t begins at one. Because equation (12) requires lagged values, it can only be estimated beginning in period two

the error terms, $E(u_{i,t}\ u_{i,t+1}) = 0$. [8] This assumption will be tested in the specification testing section of the paper.

There is also a potential problem with the explanatory variable because $\tilde{x}_{i,t-1}$ may be correlated with $\tilde{u}_{i,t-1}$. Because our x 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 $E(\tilde{x}_{i,s}\ \tilde{u}_{i,t}) = 0$ for all $s \leq t$. In order to test this assumption we perform a Hausman test comparing our results with a regression where we relax this assumption by one time period, allowing for the possibility that the level of human capital is correlated with the contemporaneous error term.

The full set of assumptions used in the GMM estimation procedure is as follows:

$$\begin{aligned} &E(\tilde{u}_{i,t}\ \tilde{u}_{i,t+1}) = 0, \quad \forall t \\ &E(\tilde{y}_{i,s}\ \tilde{u}_{i,t}) = 0, \quad s \leq t-1 \\ &E(\tilde{x}_{i,s}\ \tilde{u}_{i,t}) = 0, \quad s \leq t \end{aligned} \tag{14}$$

In practice we perform estimation with three different instrument sets, two of which utilize a subset of our assumptions. For all three regressions, all lags of y which are valid instruments are utilized. The difference lies in our use of lagged values of x as instruments.

The first instrumentation scheme, labeled GMMa, uses all orthogonal lags of the x observations as instruments. In theory, this makes estimation of the coefficient on lagged y more efficient. This scheme relies on all the assumptions listed above including the predeterminacy of x.

Monte Carlo simulations indicate that while additional instruments increase efficiency of the GMM procedure, they also may increase bias in short panels. For the second regression, labeled GMMb, the differenced x values are instrumented on themselves, without using any additional lags as instruments. This instrumentation scheme also requires the predeterminacy of x.

The third instrumentation scheme is similar to the first, in that lagged x values are used as instruments. However, 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 $E(\tilde{x}_{i,t}\ \tilde{u}_{i,t}) \neq 0$ is allowed. This estimation is performed primarily as a test of the stronger predeterminacy assumption.

If the strong predeterminacy assumption is correct, all three instrumentation schemes are consistent and should produce statistically similar coefficient values. In the next section, we will show that this is the case.

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

4 Results

The results of the GMM estimation are contained in Table 3.

	GMMa	GMMb	GMMc
ρ	0.865	0.627	0.858
(s.e)	(0.070)	(0.138)	(0.080)
β	0.768	0.672	1.039
(s.e)	(0.096)	(0.225)	(0.267)
implied λ	0.029	0.093	0.031
(s.e.)	(0.016)	(0.044)	(0.019)
implied ϕ	5.673	1.801	7.338
(s.e.)	(3.183)	(1.135)	(1.512)
Sargon Stat	36.58	20.17	34.09
DOF	33	14	28
p-value	(0.31)	(0.13)	(0.20)

Table 3: Regression Results

The reduced form coefficients are significant at the 1% level for all three regressions. The coefficient on lagged productivity, our estimator for convergence, is significantly away from one at the 1% level for GMMb, just below the 5% level for GMMa and at the 10% level for GMMc. The recovered convergence coefficient, λ, is significant at the 10% level for all three estimators and at the 5% level for GMMb.

Because the recovered elasticity of human capital is a nonlinear function of ρ and β, $\phi = \beta/(1-\rho)$ and ρ is close to one, our ϕ estimates are quite unstable. For this reason, ϕ is only significant for the more efficient GMMa estimates, at the 10% level, and the three estimates vary widely.

For all three regressions, the Sargan test of overidentifying restrictions indicates that we cannot reject the hypothesis that our identification assumptions are valid. [We need to add tests for serial correlation]

The second regression, GMMb, was performed because Monte Carlo simulation by Kiviet (1995), Judson & Owen (1996) show that the smaller instrument set often results in lower bias for ρ. However, the same studies show that the bias is always negative. Our results show that the full instrument set results in a higher estimate for ρ. Therefore we conclude that GMMb does not improve our estimate in term of reducing bias and, since it suffers from greater inefficiency, we prefer GMMa.

The third regression was performed as a test of the assumption that $E(\tilde{x}_{i,t}\ \tilde{u}_{i,t}) = 0$. A Hausman test cannot reject the null hypothesis that $\theta_a = \theta_b$, where $\theta' = (\rho \quad \beta)$. We therefore conclude that the stronger predeterminacy assumption embodied in GMMa is valid. For these reasons, we will concentrate on the more efficient GMMa estimates though almost all our conclusions hold for all three estimators.

We draw two primary conclusions from the results. First, the significance of λ 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.

Second, though ϕ is only marginally significant, we take the significant coefficient on β to indicate that the level of human capital has a large positive effect on a country's ability to take advantage of spillovers. This conclusion is compatible with the theoretical work of Nelson & Phelps (1966) and others. Countries with higher levels of human capital converge to a higher steady state level of productivity.

5 Specification and Robustness tests?

Some of the statistical claims in the last section need more exposition and we need a few more test. In particular a test of serial correlation (pass) and a test that x is strictly exogenous (fail)

We also can do a bunch of robustness checks, such as splitting the sample by time period (early/late split results in a somewhat faster convergence coefficient, but nothing to contradict the results) OECD/nonOECD, etc.

6 Fixed Factors, Human Capital and Steady-State Productivity

It is interesting to examine, on the heels of the last section, how much of the variation in steady state 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:

$$\widehat{f}_i = \frac{1}{T}\sum_{t=1}^{T}(y_{i,t} - \widehat{\rho}y_{i,t-1} - \widehat{\beta}x_{i,t-1} - \widehat{\eta}_t) \tag{15}$$

Further, from equation (6), taking account of our panel notation, it is apparent that we may write:

$$\log A^*_{i,t} = \log F_i + \phi \log h_{i,t-1} + T(t) \tag{16}$$

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

$$\overline{\log A}^*_{i,t} = \overline{\log F}_i + \phi \overline{\log h}_{i,t-1} \qquad (17)$$

From equation (17) it is possible to obtain a full set of estimates for the steady state TFP of each country in each five year period (in deviations from country means) except for the earliest one [9]. Appendix 3 includes a full list of these steady state levels.

A puzzling feature of the fixed effects that we recover is that their covariance with human capital is negative in each one of our time periods. Our prior expectation would be to the contrary; on the face of it one would expect to find a positive correlation between the two, if one believes that countries with high stocks of human capital are also those that enjoy favorable social and legal infrastructures of the type that may be thought to enter into the fixed effect. One possible explanation for this is that there are other, time-varying factors that influence the dynamics of TFP and that are negatively correlated with human capital which we are omitting from our analysis, thereby biasing the correlation between human capital and the fixed effects. At any rate, this result needs further thought to interpret, and will hopefully be clarified by further research.

The negative correlation between our fixed effects and human capital is large enough that $cov(\overline{\log A}^*_i, \overline{\log F}_i)$ is negative in most periods and small in every period. This implies that an exercise of the type reported in section II, dividing the variance in $\overline{\log A}^*_i$ into that attributable to $\overline{\log F}_i$ and that attributable to $\phi\overline{\log h}_i$ is difficult to interpret as a variance decomposition. However, recall that the terms $\frac{cov(\overline{\log A}^*_i, \overline{\log F}_i)}{var(\overline{\log A}^*_i)}$ and $\frac{cov(\overline{\log A}^*_i, \phi\overline{\log h}_i)}{var(\overline{\log A}^*_i)}$ may be interpreted as the OLS coefficients from independent regressions of the fixed factors and human capital stocks respectively on steady state TFP levels. We find that $\frac{cov(\overline{\log A}^*_i, \phi\overline{\log h}_i)}{var(\overline{\log A}^*_i)}$ ranges between 0.87 in 1965 and 1.15 in 1985, with a value of 1.04 in 1990. That is to say, had we in 1990 identified a country with a steady state TFP level 1% greater than the mean across countries, we would expect it to have had a 1% higher stock of human capital in 1985 relative to the mean stock of human capital across countries. On the other hand, the coefficient obtained by regressing the fixed factors on steady state TFP levels ranges from 0.13 in 1965 to -0.15 in 1985, but these coefficients are insignificant in every year of our sample, with a t-statistic well below unity in every case.

It needs to be emphasized that we regard the above results as indicative rather than definitive. The exercise is quite sensitive to the value chosen for ϕ, and, as we have

[9] The fact the steady state 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.

seen in the previous section, our point estimate for ϕ lacks precision to some extent. Nonetheless, our results certainly seem to bear out the hypothesis that there is a strong and positive qualitative relationship between human capital stocks and steady state TFP, even if we are not entirely confident of the numerical strength of the relationship. In conjunction with the results of section IV, we conclude that there is good evidence that human capital has a dynamic effect on total factor productivity, that this effect is strong and positive, and that therefore to examine the relationship between human capital and per capita income only in light of the direct effect of the former on the latter as an accumulable factor in the production function is to miss the most crucial link between growth and education.

7 Conclusion

We began this paper by retracing the debate about the relative importance of TFP and factor accumulation in the growth process. While MRW 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 reconciles these two conflicting points of view in some measure. While we show in section II that TFP differences are indeed important in accounting for variations in income, in subsequent sections we show that human capital plays a significant role determining a country's *potential* TFP level. Add to that our result that conditional convergence to steady state TFP levels is indeed occurring, and it follows that human capital is a crucial ingredient in 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 have argued here that international technology spillovers from countries at the frontier to countries that are attempting to catch-up are facilitated by the human capital stocks of the host nation. We do not doubt that other factors, too, may facilitate the ease with which imitation may be carried out. 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 that it invites and embraces, macroeconomic stability and the prevalence of the rule of law; all of these are promising candidates. We suspect, too, that further research in these directions would help knit together some of the threads left loose by this study; in particular the negative correlation that we find between our fixed factors and stocks of human capital.

We also believe that it would be interesting to do case studies of countries that stand as counterexamples to the kinds of processes described here, such as Sri Lanka, which enjoys almost universal literacy and yet lags behind in the realm of per capita income .

In light of the analysis here, we may pose the conundrum as follows: Have Sri Lanka's high stocks of human capital failed to translate into commensurately high target TFP levels? If so, why? Or is it the case, as seems more likely, that there are other factors at work in Sri Lanka, perhaps related to economic policy, that are preventing rapid convergence and maintaining a large gap between potential and actual TFP levels?

Finally, we believe that further research into the measurement of human capital is likely to be very beneficial to growth empirics. Our study here 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. In particular, our study here cannot identify the relative importance of different tiers of education - elementary, secondary and higher - on TFP convergence. Such work must await both more detailed data, and a more thorough conceptual understanding of how to measure and aggregate different *kinds* of human capital.

Appendix 1: 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 siutable 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: .0146, .0133, .0189, .0136, .0153, .0164 and .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.

Appendix 2: GMM Estimation

We can rewrite equation (13) as

$$Y_{i,t} = X_{i,t}\ \theta + v_{i,t} \tag{18}$$

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

$$Y_i = \begin{bmatrix} \Delta\tilde{y}_{i,3} \\ \vdots \\ \Delta\tilde{y}_{i,T} \end{bmatrix}, \quad X_i = \begin{bmatrix} \Delta\tilde{y}_{i,2} & \Delta\tilde{x}_{i,2} \\ \vdots & \vdots \\ \Delta\tilde{y}_{i,T-1} & \Delta\tilde{x}_{i,T-1} \end{bmatrix} \tag{19}$$

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

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

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

$$E(\tilde{y}_{i,s}\ v_{i,t}) = 0, \quad s \leq t-2 \tag{20}$$

$$E(\tilde{x}_{i,s}\ v_{i,t}) = 0, \quad s \leq t-1 \tag{21}$$

For $t = 3$, the first period for which all lags are available, these orthogonality conditions indicate that $y_{i,1}, x_{i,1}$ 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

$$Z_i^a = \begin{bmatrix} \tilde{y}_{i,1}\ \ \tilde{x}_{i,1}\ \ \tilde{x}_{i,2} & & & 0 \\ & \tilde{y}_{i,1}\ \ \tilde{y}_{i,2}\ \ \tilde{x}_{i,1}\cdots\tilde{x}_{i,3} & & \\ & & \ddots & \\ 0 & & & \tilde{y}_{i,1}\cdots\tilde{y}_{i,5}\ \ \tilde{x}_{i,1}\cdots\tilde{x}_{i,6} \end{bmatrix} \tag{22}$$

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

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

$$Z_i^b = \begin{bmatrix} \tilde{y}_{i,1} & & & 0 & \Delta\tilde{x}_{i,2} \\ & \tilde{y}_{i,1}\ \ \tilde{y}_{i,2} & & & \Delta\tilde{x}_{i,3} \\ & & \ddots & & \vdots \\ 0 & & & \tilde{y}_{i,1}\cdots\tilde{y}_{i,5} & \Delta\tilde{x}_{i,6} \end{bmatrix} \tag{23}$$

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

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 θ is

$$\hat{\theta}_j = (X'ZA_jZ'X)^{-1}X'ZA_jZ'Y \tag{25}$$

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

$$A_1 = \left(\frac{1}{N} \sum_{i=1}^{N} Z_i' H Z_i \right)^{-1} \tag{26}$$

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 θ, $\hat{\theta}_1$ can be found using (25). The first stage estimated errors, $\hat{v^1} = Y - X\hat{\theta}_1$ can be used to calculate a second stage weight matrix,

$$A_2 = \left(\frac{1}{N} \sum_{i=1}^{N} Z_i' \hat{v^1}_i \hat{v^1}_i' Z_i \right)^{-1} \tag{27}$$

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

$$V_j = N(X'ZA_jZ'X)^{-1}X'ZA_j \left(\sum_{i=1}^{N} Z_i'\hat{v}_i\hat{v}_i'Z_i \right) A_jZ'X(X'ZA_jZ'X)^{-1} \tag{28}$$

which simplifies in the second stage to

$$V_2 = N(X'ZA_2Z'X)^{-1} \tag{29}$$

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