Review of Income and Wealth
Series 49, Number 2, June 2003

PRODUCTIVITY DYNAMICS IN A LARGE SAMPLE OF COUNTRIES: A PANEL STUDY

BY NAZRUL ISLAM

Emory University

Recent research shows that productivity differences are more important than differences in accumulation rates in explaining per capita income differences across countries. So far *static* differences in productivity have been mainly computed and analyzed in large samples of countries. This paper extends the research by focusing on productivity *dynamics*. It uses the panel approach to compute productivity indices for a large sample of countries for two time periods, namely an initial period of 1960–75 and a subsequent period of 1975–90. This allows computation of ordinal and cardinal *changes* in productivity between the two periods. The results show considerable variation in productivity dynamics across countries. The task ahead is to find out what accounts for the observed dynamics.

1. INTRODUCTION

Recent research shows that productivity differences are more important than differences in input intensity in explaining per capita income differences across countries. Some studies indicate that productivity levels of developed countries have converged. However, studies also indicate that such convergence has not occurred either among developing countries themselves or between them on the one hand and developed countries on the other. This makes study of productivity dynamics in large samples of countries more interesting and useful.

Several different approaches have been used so far for international comparison of total factor productivity (TFP). Among these are the time-series growth accounting approach, the panel regression approach, and the cross-section growth accounting approach. Data limitations do not allow application of the sophisticated version of the time series approach to most developing countries. The panel regression approach was used earlier in Islam (1995) to produce productivity indices for a sample of 96 countries. Recently Hall and Jones (1996, 1999) have used the cross-section growth accounting approach to produce productivity indices for 127 countries for the year of 1988.

However, such *static*, snapshot pictures cannot provide productivity *dynamics*. Yet it is dynamics that can better reveal the determinants of productivity. This paper applies the panel approach to produce productivity indices for two different time periods and thereby quantifies productivity *changes*. The sample consists of 83 countries for which Penn World Tables (PWT) allow construction of

Note: I would like to thank participants of seminars at Emory University and Georgia State University where this paper was presented. I am thankful to the anonymous referee for very helpful comments. All remaining errors and shortcomings are however mine. Please send your comments to nislam@emory.edu.

*Correspondence to: Nazrul Islam, Department of Economics, Rich Building 306A, Emory University, Atlanta, GA 30322-2240, USA (nislam@emory.edu).

five-year panels ranging from 1960 to 1990. The two sub-periods distinguished are (a) an "initial" (or "earlier") sub-period ranging from 1960 to 1975; and (b) a "subsequent" (or "later") sub-period ranging from 1975 to 1990.

The estimated parameter values used for productivity index computation indicate that the value of the capital share parameter for the later period is considerably higher than for the earlier period. Two possible explanations for this increase are: (a) shift in distribution in favor of capital; and (b) greater role of human capital in the production process in the subsequent period compared with that of the initial period.

Ordinal and cardinal indices of productivity change computed on the basis of the estimated parameter values reveal wide variation in productivity dynamics across countries. An encouraging aspect of the result is that a large number of countries are found to have improved their relative productivity level *vis-à-vis* that of the leading country, namely the U.S. Unfortunately the magnitude of improvements is small so that the bulk of the countries remain far removed from the U.S. productivity level in the subsequent period as they were in the initial period. This leads to the phenomenon of "persistence." Many countries that are in the top-ten list of the productivity rung in the initial period continue to be in this list in the subsequent period, and similarly for the bottom-ten list. Countries of the top-ten list are mostly from Europe and North America. However Hong Kong enters this list in the later period. Countries of the bottom-ten list are mostly from sub-Saharan Africa. However, India is also in this list, showing that high investment rates do not always go together with productivity growth.

On the other hand, there are countries that do experience large improvements in their relative productivity level. Among them are some of the East Asian countries, such as Hong Kong, Singapore, and Korea, indicating that alongside accumulation, productivity improvements also played a role in these countries' recent economic growth. In fact, Hong Kong's spectacular productivity performance pushes it to the second position in the productivity rung in the later period. At the other end, there are a number of countries whose relative productivity levels decline between the periods. Many of these are Latin American countries.

This wide variation in productivity performance leads to considerable churning in ordinal productivity ranking of countries. In fact as many (36) countries witness improvement in their productivity rank as experience deterioration.

Indices of productivity level and change presented in this paper of course need to be taken with some caution. First, results of any empirical exercise are often as good as the data used for the purpose. The PWT, despite their widespread use and their purchasing power parity (PPP) feature, have drawn some criticisms too. There are researchers who doubt the validity of these data and question the merit of research done on their basis. While we do not share the extreme variants of this criticism, we recognize that some aspects of the results presented in this paper may owe more to data construction than to the genuine economic processes of interest. Second, there may be scope for further improvement in the methodology.

Despite these potential shortcomings, the paper shows that it is possible to move the analysis of international productivity differences forward from that of *levels* to that of *changes*. Instead of limiting to a *static* snapshot, it is possible to capture the *dynamics*. Information regarding these dynamics presented in this paper can provide a point of departure for a second stage analysis focused on ascertaining the determinants of productivity. Human capital can play an important role in this second-stage analysis, which can be cross-sectional in nature. This suits well with the available human capital data that seem to contain more information along the cross-section dimension than along the time-dimension. Such a second stage analysis and dealing with the remaining methodological issues of computation of productivity indices are two important lines along which future research can proceed.

The paper is organized as follows. Section 2 provides the background to the study. Section 3 discusses various issues related to the panel approach to productivity study. Section 4 presents the estimation of parameter values. Section 5 presents and discusses the indices of productivity levels and changes. Section 6 draws the conclusions.

2. Importance and State of International Productivity Study

Some recent studies have shown that productivity[1] levels of developed countries have largely converged to each other.[2] This *productivity-convergence* has been portrayed as part of the *income-convergence* process among developed countries.[3] However, research has also shown that income-convergence and productivity-convergence have not occurred either among developing countries themselves or between them on the one hand and developed countries on the other. In other words, large productivity differences exist among countries of a global sample, and it is these productivity-differences, rather than differences in input intensity, that account for the greater part of the observed per capita income-differences across countries. For example, Hall and Jones (1999) note that of the 35-fold difference in per capita income between the U.S. and Nigeria, the difference in capital intensity accounts for a factor of 1.5, and the difference in educational level accounts for another factor of 3.1. Productivity difference accounts for the remaining 7.7 factor. Similar large differences in productivity were reported earlier in Islam (1995), where the productivity level of the best performing country was found to be 39 times higher than that of the worst performing country. Accordingly, study of productivity differences in large samples of countries can provide more insights regarding determinants of productivity.

Separating out the contribution of total factor productivity from that of input growth is however a thorny issue. Many large debates have been waged on this

[1]In this paper by "productivity" we shall generally mean "total factor productivity" (TFP) or what is sometimes also called "multi-factor productivity," and not "labor productivity," which can be approximated by per-capita income.

[2]See for example, Dougherty and Jorgenson (1997).

[3]There is a "selection" problem in the analysis of convergence in small samples of developed countries. See De Long (1988) and Baumol and Wolff (1988) for a discussion of this issue.

subject, and these debates still continue.[4] Even within the tradition of the aggregate production function framework, several methodological approaches to the study of productivity have emerged. These are: (a) the "time series growth accounting approach," (b) the "panel regression approach," and (c) the "cross-section growth accounting approach."[5] The "time-series approach," starting with Tinbergen (1942/1959), has attained a great degree of sophistication in the hands of Jorgenson and his associates.[6] However, data limitations restrict application of this approach to many developing countries. This, in part, led to the emergence of the panel and cross-section approaches. Islam (1995) uses the panel regression approach to estimate productivity levels in a sample of 96 countries. Hall and Jones (1996, 1999), on the other hand, use the cross-section growth accounting approach to compute productivity levels in a sample of 127 countries.

Despite this progress, productivity indices computed for large samples of countries have been so far limited to only one particular time period.[7] Yet, growth researchers have now extended their interest beyond such "proximate" sources of growth as investment rate and labor force growth rate. They are currently searching for *ultimate* or *fundamental* sources of growth.[8] One-shot pictures of productivity differences are not adequate for this purpose. Productivity analysis based on one-shot indices has to substitute cross-section variation for temporal change. This limits the analysis. In order to identify the fundamental sources of productivity, it is necessary to unearth, document, and analyze productivity *dynamics*. This paper takes a step in that direction. We begin by discussing the arguments for using the panel approach and the issues that arise in using this approach.

3. The Panel Approach to Productivity Study

The Cross-section vs. the Panel Approach

A comparison between the cross-section growth accounting approach and the panel regression approach shows that both have their methodological strengths

[4]Many researchers are skeptical about using aggregate production function in computing total factor productivity. (See for example Felipe (1999) for a recent discussion.) Others contend that it is not possible to separate out contribution of productivity from that of the inputs even within the aggregate production framework. See for example, Abramovitz (1956, 1993) and Abramovitz and David (1973). Wolff (1991) discusses this issue in a cross-country setting. Despite these reservations, total factor productivity continues to be studied, and the aggregate production function continues to be the dominant paradigm within which this study is conducted. This is, in part, because of Solow's (1957, 1962) advice to accept the aggregate production function as a useful parable necessary to learn the lesson, if not the whole truth. Another reason for the prevalence of the aggregate production function approach is the lack of appealing alternative operational concepts allowing quantification of productivity differences across economies.

[5]See Islam (1999) for a recent review of these approaches. Another approach to productivity analysis and efficiency comparison is often referred to as the stochastic frontier production function (SFPF) approach. Important works using this approach include Fare *et al*. (1994) and Nishimizu and Page (1982). However, application of this approach requires data that are not available for large samples of countries.

[6]See for example, Jorgenson (1995a) and (1995b). Wolff (1991) and Dollar and Wolff (1994) also use the time-series growth accounting approach to investigate convergence in small samples of developed countries. Dougherty and Jorgenson (1996, 1997) present recent time-series investigations of convergence among G-7 countries.

[7]For example, the productivity level estimates of Hall and Jones (1996, 1999) are for 1988. Those of Islam (1995) are for the 1960–85 period as a whole. These provide *one-shot* pictures of relative productivity levels across countries.

[8]See for example, Barro (1997), Hall and Jones (1999), and Sachs and Warner (1997).

and weaknesses.[9] One merit of the cross-section growth accounting approach implemented in Hall and Jones (1996) was that it allowed for the capital share parameter, α, to differ across countries. This however required the assumption of a common rate of return to capital for all countries. The method also required prior ordering of countries according to some criterion. The productivity results obtained on the basis of these assumptions yielded some surprising candidates at the apex of the productivity ranking. In Hall and Jones (1999) the authors abandon the country specific α values and opt for a common value of α. However, they choose the value of α arbitrarily. From this point of view, the panel regression approach has certain advantages. It also assumes a common value of α for the sample. However, instead of imposing this value arbitrarily, the panel approach lets the sample data determine the best-fit value of α. Also, the cross-section growth accounting approach requires construction of capital stock data, which in turn requires assumptions regarding initial capital stock values and depreciation profiles. These may act as additional sources of noise in the data. The panel regression approach on the other hand can work directly with investment rates.[10] All these considerations lead us to use the panel approach in this study, though this does not mean that other approaches are not viable.

Issues of the Panel Approach

The panel regression approach itself however has many issues. This approach originated from the fact that the growth-convergence equation can be reformulated as a dynamic panel data model. Proceeding from the following Cobb–Douglas production function with Harrod-neutral technological progress

$$Y_t = K_t^{\alpha}(A_t L_t)^{1-\alpha}, \tag{1}$$

where Y, K, and L are output, capital, and labor respectively, and A is the labor-augmenting technology which grows exponentially at the rate g, it is possible to derive the following dynamic panel data equation.[11]

$$y_{it} = \gamma\, y_{i,t-1} + \beta x_{i,t-1} + \mu_i + \eta_t + v_{it}, \tag{2}$$

where y_{it} represents log of per capita GDP of country i at time t, $y_{i,t-1}$ is the same lagged by one period, and $x_{i,t-1}$ is the difference in log of investment and labor force growth rate variables of country i at time $t-1$. Finally, μ_i is the individual *country effect*, η_t is the time (period) effect, and v_{it} is the transitory error that varies across both country and period. The correspondence between coefficients of equation (2) and the parameters of the production function given by equation (1) is as follows:

$$\gamma = e^{-\lambda\tau}, \tag{3}$$

[9]Islam (1999) provides a more detailed discussion.

[10]Also of note is that Hall and Jones have now moved away from the Hicks-neutral specification of technological progress that they used in their earlier (1996) paper. In Hall and Jones (1999), they adopt the Harrod-neutral specification, which has been also the specification of choice by most of the panel studies of growth.

[11]The derivation of this equation is available in many recent papers and hence is not reproduced here. See for example Barro and Sala-i-Martin (1992, 1995), Mankiw, Romer, and Weil (1992), Islam (1995), Mankiw (1995), and the related papers.

(4) $$\beta = (1 - e^{-\lambda\tau})\frac{\alpha}{1-\alpha},$$

(5) $$\mu_i = (1 - e^{-\lambda\tau})\ln A_{0i}, \text{and}$$

(6) $$\eta_t = g(t_2 - e^{-\lambda\tau}t_1).$$

Here, τ is the length of time between t_2 and t_1, which correspond to t and $(t - 1)$, respectively, of equation (1). Finally, $\lambda = (1 - \alpha)(n + g + \delta)$. Panel estimators can now be used to estimate the parameters of equation (2), which can then be used to recover the value of the productivity level, A_i, of different countries.

Since its original application in Islam (1995) and Knight *et al.* (1993), the panel approach to empirical study of growth has seen widespread application. This has also led to some controversies. For example, Barro (1997) expresses the view that panel estimation is not appropriate for estimation of the growth-convergence equation, because it throws away the cross-section variation and relies only on the "within" variation. This contention however is true mainly for the least squares with dummy variables (LSDV) estimator, which is based on the *fixed-effects* assumption. Most of the other panel estimators use both "within" and "between" variation. Also, it is a moot point whether the *between-variation* or the *within-variation* is more appropriate for estimation of the convergence parameter.[12]

Nerlove (1999) highlights the issue of small sample bias in the context of panel estimation of the growth-convergence equation. He explores with a variety of panel estimators and finds significant difference in results from their application. However, except for LSDV, all estimators considered by Nerlove rely on the *random-effects* assumption. Yet, it is important to note that the random-effects assumption regarding the country-effect term, μ_i, is not appropriate for the growth-convergence equation. In typical specifications of this equation, the right hand side variables include savings rate, labor force growth rate, etc., which are generally correlated with μ_i. In fact, it is this correlation that in the first place led to the abandonment of the cross-section regression and adoption of the panel approach.

Also, large samples used to estimate the growth-convergence equation often include all notable countries of the world. This implies that almost the entire population is included in estimation, thus leaving little scope for random sampling of μ_i. Finally, the de Finiti condition of interchangeability is not satisfied in the context of the growth-convergence equation. For example, it is difficult to argue that such components of μ_i as institutions and resource endowments of the U.S. and Sierra Leone can be interchanged without affecting the growth outcome in any significant way. All these considerations suggest that panel estimators based on random-effects assumption are not suitable for estimating the growth-convergence equation.

There are however some panel estimators that proceed by first-differencing equation (2). This yields the following equation, which no longer includes the country effect term μ_i.

(7) $$(y_{it} - y_{i,t-1}) = \gamma(y_{i,t-1} - y_{i,t-2}) + \beta(x_{i,t-1} - x_{i,t-2}) + (\eta_t - \eta_{t-1}) + (\nu_{it} - \nu_{i,t-1}).$$

[12]See Islam (2003) and Ventura (1997) for discussions of this issue.

For estimators that proceed from equation (3) it therefore matters less whether the μ_i's are random or not. Anderson and Hsiao (1981, 1982) take this approach and use further lagged values of the dependent variable as instruments. Arellano and Bond (1991) extend this idea and suggest using all possible lagged values of the dependent variable as instruments in a GMM framework. Others have gone further. For example, Ahn and Schmidt (1995) show that there are non-linear moment conditions that are not exploited in Arellano–Bond, and efficiency can be improved by using them.

One theoretical advantage of estimation with further lagged variables as instruments is that it helps avoid potential endogeneity problem that has been emphasized by Caseli *et al*. (1996). Equation (2) by itself does not suffer from endogeneity problem if the explanatory variable is $x_{i,t-1}$ (which is the theoretically correct form) instead of x_{it}. However, the problem may still arise if the estimator requires strict exogeneity of x_{it}. From this point of view GMM estimators that use only predetermined values of the variables as instruments have some advantage.

Estimation of dynamic panel data models with further lagged variables as instruments has received considerable attention in recent years. Arellano and Bover (1995) suggest transformation of the system using the "forward orthogonal deviations operator" and then using lagged values of predetermined variables as instruments. Keane and Runkle (1992) suggest the forward filtering method of Hayashi and Sims (1983) as an alternative way of conducting panel estimation with pre-determined variables, including lagged dependent variables. They show that this method can be applied even to the level-equation when individual-effects are *random*. On the other hand, if individual effects are fixed and correlated, the method has to be applied to the first-differenced equation. Schmidt, Ahn, and Wyhowski (1992) show that filtering becomes irrelevant if all available instruments are used. GMM estimators that proceed from first-differenced equation are now referred to as GMM-DIF estimators. Caseli *et al*. (1996) actually use an Arellano–Bond (1991) type GMM-DIF estimator to estimate the growth-convergence equation.

The problem with GMM-DIFF estimators however is that they have been found to have significant small sample bias. Such bias has been reported in Alonso-Borrego and Arellano (1999), Kiviet (1995), Harris and Matyas (1996), Islam (2000), Judson and Owen (1997), Ziliak (1997) and several other studies. Ziliak (1997) presents an application of several panel estimators in a situation of pre-determined variables. He finds that GMM estimators suffer from severe bias, though the forward-filter GMM estimator performs better. These results suggest that the results of Caseli *et al*. (1996), obtained by use of a GMM-DIF estimator, may suffer from small sample bias.

Partly in view of the small sample bias of GMM-DIFF estimators, Blundell and Bond (1998) offer a System GMM estimator (referred to as GMM-SYS). They show that several restrictions on initial variables yield more linear moment conditions, and a GMM estimator inclusive of these conditions encompasses Ahn and Schmidt's non-linear GMM estimator. The GMM estimator proposed by Blundell and Bond adds equations in *levels* to the original system of equations in first differences and uses first differences of lagged variables as instruments for the level equations. Blundell and Bond's own work (1998) shows GMM-SYS to have better small sample performance than that of GMM-DIFF. However it is not known whether this superiority will hold in the concrete case of estimation of the growth-convergence equation using PWT data.

On the other hand, several studies have shown good small sample performance of Chamberlain's (1982, 1983) Minimum Distance (MD) estimator. This estimator takes an opposite approach to the individual effect μ_i. Instead of avoiding the issue correlation of μ_i's with x_{it}'s by eliminating μ_i through first-differencing of equation (2), the MD estimator highlights this correlation and offers a very general specification of μ_i in terms of x_{it}'s. This leads to a multivariate system with as many cross-section equations as time periods available. Estimation of this system yields the Pi-matrix of reduced form coefficients. In the second stage of MD estimation, estimates of the structural parameters are squeezed out of the elements of the Pi-matrix using the Minimum Distance framework. The MD estimator also lets the error variance-covariance matrix be perfectly general and hence is robust to presence of heteroskedasticity across units (countries) and autocorrelation across different time periods for the same unit (country). The Monte Carlo study by Islam (2000) shows better performance of the MD estimator in estimating the growth-convergence equation using the Penn World Table (PWT) data.

Interestingly, Monte Carlo study shows very good performance of the LSDV estimator too. This is despite the fact (as shown by Nickell (1981) and others) that, in a model with lagged dependent variable, the LSDV estimator is consistent only in the direction of T and not N. Kiviet (1995) has recently worked out some analytical results regarding the small sample bias of the LSDV estimator and has proposed a bias-corrected LSDV. His simulations show that the bias-corrected LSDV performs better than GMM-DIF type estimators do. Judson and Owen (1997) reach similar conclusions. In this paper we make use of several estimators, including MD, LSDV, and GMM-SYS estimator.

4. Estimation and Results

The paper focuses on the 98-country sample that has figured widely in recent growth and productivity studies.[13] It begins by constructing five-year panels in similar fashion as in Islam (1995). The main reason for considering data in five-year panels instead of the yearly form is to minimize the role of the short-term (business cycle) fluctuations in the estimation of long run growth parameters. The recent version of the Penn World Tables allows the time period to be extended to 1990. For reasons that will soon be clear, having another five-year panel covering the 1990–85 period is important for estimation purposes of the paper. Unfortunately, not all countries of the original 98-country sample have data for the year 1990. Hence, we have to drop 13 countries for which data are missing, reducing the sample size to 83. The entire period extends from 1960 to 1990, and we have six five-year panels, namely 1990–85, 1985–80, 1980–75, 1975–70, 1970–65, and 1965–60. Appendix Table A1 provides the list of countries included in the sample.

While $T = 6$ is a reasonable size (with $N = 83$) for MD estimation, our task is made difficult by the fact that we need to distinguish two sub-periods in order to

[13]See for example, Barro (1991), Mankiw, Romer, and Weil (1992), and Islam (1995).

reveal changes in productivity over time. The two sub-periods distinguished are an "initial" (also referred as "earlier") sub-period consisting of the panels for 1965–70, 1970–65, and 1975–70 and a "subsequent" (also referred as "later") sub-period consisting of the panels for 1980–75, 1985–80, and 1990–85. We begin by considering first results obtained from the model that includes human capital along with physical capital.

Estimation with Human Capital

Researchers have all along recognized the importance of human capital in creation of income and in growth. Unfortunately, there is no consensus yet about the precise way in which human capital should enter the aggregate production function. Different ways of modeling human capital have different implications for the productivity term. For example, log transformation of equation (2) yields

$$\ln Y - \alpha \ln K - (1-\alpha)\ln L = (1-\alpha)\ln A^S, \tag{8}$$

where A^S indicates that this productivity term comes from the original Solow-type production function given by equation (2). As is known, K here stands for "physical capital" and L is usually measured by number of workers. Hence any contribution that human capital makes to production has to occur through its impact on A^S. In other words, productivity indices computed using equation (2) embody the impact of human capital.[14]

On the other hand, Mankiw, Romer, and Weil (1992) propose the following multiplicative and symmetric (relative to physical capital) inclusion of human capital in the production function:

$$Y = K^\alpha H^\varphi (AL)^{1-\alpha-\varphi}. \tag{9}$$

Proceeding from this equation, we have

$$\begin{aligned} \ln Y - \alpha \ln K - (1-\alpha)\ln L &= (1-\alpha-\varphi)\ln A^{MRW} + \varphi(\ln H - \ln L) \\ &= (1-\alpha)\ln A^{MRW} + \varphi(\ln h - \ln A^{MRW}) \end{aligned} \tag{10}$$

where h is human capital per unit of L, and we add superscript MRW to the term A in order to distinguish it from A^S. Together with (8) this implies that

$$\ln A^S = \left(\frac{1-\alpha-\varphi}{1-\alpha}\right)\ln A^{MRW} + \frac{\varphi}{1-\alpha}\ln h. \tag{11}$$

This shows clearly that productivity (A^S) computed using equation (2) contains a human capital component that is left out of A^{MRW}.

Hall and Jones (1999) propose yet another way of including human capital in aggregate production functions. According to their proposal

$$Y = K^\alpha (A^{HJ} H)^{1-\alpha}, \tag{12}$$

where H is specified to be $e^{\phi(E)}L$, with E being years of education. With this specification, the relationship between A^S and A^{HJ} is simply as follows:

[14]Here we are referring to usual cross-country exercises of productivity computation. In their study of productivity in the U.S. and other developed counties however Jorgenson and his associates have allowed for quality differences in both capital and labor. In this setup, human capital can enter the picture even through L.

$$\ln A^S = \ln A^{HJ} + \phi(E). \tag{13}$$

This problem of lack of consensus about the way in which human capital should enter the aggregate production function is of theoretical nature. From the point of view of computation of productivity indices however this problem may be less serious, because, as the above algebra demonstrates, we can ascertain how productivity indices obtained from use of different production functions relate to each other.

There is however a second and more serious problem concerning inclusion of human capital in computation of productivity in a large sample of countries. This relates to the measurement of human capital. Available cross-country data on human capital are plagued with problems, as highlighted again by Krueger and Lindahl (2001) in their recent survey paper. Referring to human capital measures used in Benhabib and Spiegel (1994), Krueger and Lindahl note that ". . . there is virtually no signal in education data they use, conditional on the growth of capital" (p. 1102). Fortunately, measurement errors do not swamp the *cross-section* variation in human capital data, so that human capital still displays the theoretically correct, positive impact on growth in *cross-section* regressions. By comparison, measurement errors seem to be quite serious with respect to the *time series* dimension of human capital data, and that is why regressions striving to decipher impact of *change* in human capital on growth have usually met with disappointing results. This has been true both with panel regressions as in Benhabib and Spiegel (1994) or Islam (1995) and with pooled regressions, as in DeGregorio (1992). In view of these measurement error problems, available human capital variables are not expected to play out well in panel computation of productivity indices.

Nevertheless, we begin the analysis with human capital included in the model, and we do so using the Mankiw, Romer, and Weil (1992) specification given by equation (9). As shown in Islam (1995), proceeding from this specification, the growth-convergence equation analogous to (2) solves out to be as follows:

$$y_{it_2} = \gamma\, y_{it_1} + \beta_2[\ln(s_{kit_1}) - \ln(n_{it_1} + g + \delta)] + \beta_3 \ln(h^*_{it_1}) + \mu_i + \eta_{t_2} + \nu_{it_2}, \tag{14}$$

where the notations are as before, and h^* is the steady state value of per capita human capital. The correspondence between reduced form coefficients of equation (14) and parameters of the human capital augmented production function of equation (9) are as follows:

$$\lambda = -(\ln\gamma/\tau) \tag{15}$$

$$\alpha = \beta_2/(1-\beta_1+\beta_2) \tag{16}$$

$$\varphi = \beta_3/(1-\beta_1+\beta_2). \tag{17}$$

Table 1 presents results from estimation of the model with human capital.[15] The first panel of the table provides estimates of coefficients of equation (14). The second panel provides implied values of factor share parameters, α (of physical capital) and φ (of human capital). Looking at estimated values of these parame-

[15]These results are obtained using the simplest of the panel estimators, namely LSDV. This is because the model with human capital has more parameters and hence is not easy to estimate using more sophisticated panel estimators such as the MD estimator or the GMM-SYS estimator.

TABLE 1

PANEL ESTIMATION OF THE MODEL WITH HUMAN CAPITAL

	Initial period (1960–75)		Subsequent period (1975–90)	
	Without Human Capital	With Human Capital	Without Human Capital	With Human Capital
No. of obs.	249	221	249	227
No. of countries	83	75	83	76
$\hat{\gamma}$	0.40	0.44	0.51	0.49
	(0.07)	(0.08)	(0.06)	(0.06)
$\hat{\beta}_2$	0.15	0.15	0.25	0.25
	(0.03)	(0.03)	(0.04)	(0.04)
$\hat{\beta}_3$		−.009		−.15
		(0.07)		(0.09)
$\hat{\lambda}$	0.18	0.16	0.14	0.14
	(0.03)	(0.03)	(0.02)	(0.03)
$\hat{\alpha}$	0.20	0.21	0.34	0.33
	(0.04)	(0.04)	(0.04)	(0.04)
$\hat{\varphi}$		−.013		−.19
		(0.11)		(0.14)
R^2-within	0.67	0.71	0.48	0.46
R^2-between	0.98	0.98	0.97	0.97
R^2-overall	0.95	0.96	0.97	0.96
P (F-value)	0.00	0.00	0.00	0.00

Notes: (1) The models with and without human capital are as follows:

$$y_{it} = \gamma\, y_{i,t-1} + \beta x_{i,t-1} + \mu_i + \eta_t + \nu_{it}$$

$$y_{it_2} = \gamma\, y_{it_1} + \beta_2[\ln(s_{kit_1}) - \ln(n_{it_1} + g + \delta)] + \beta_3 \ln(h^*_{it_1}) + \mu_i + \eta_{t_2} + \nu_{it_2},$$

These are equations (2) and (14), respectively, in the text, which explains the notations.

(2) The results presented in this table are obtained using the LSDV estimator. The estimated values of the time effects (η_t) are not reported. The numbers in parentheses are standard errors.

(3) Quinquennial data on human capital are not available for several countries. This causes samples to be smaller in estimation of the model with human capital.

ters, we notice the following. First, estimated values of φ for both the periods prove negative, something that is theoretically not plausible. Fortunately the estimates prove insignificant too. Second, estimated values of α obtained from the model with human capital do not differ that much from those obtained from the model without human capital. These two facts together imply that the time-dimension of human capital data do not prove that useful in revealing human capital's impact on growth. We will therefore focus in this paper on estimation of productivity indices representing A^S as obtained from equation (2).

This does not mean that human capital cannot enter the analysis suggested by this paper. As proposed in Islam (1996, 2003), productivity indices presented in this paper and elsewhere can provide the point of departure for a *second stage* analysis, where these indices are examined to find out determinants of productivity. Evidently, human capital will have a prominent place in this second stage analysis, which can be cross-sectional in nature. This fits well with available human capital data, because as we just noticed, the cross-section dimension of these data seems to contain more signal than their time dimension does. Thus estimated values of A^S and change in A^S can be regressed on human capital and other relevant variables to find out the role of human capital in productivity and growth.

Several researchers, such as Hojo (2002), have already followed this route and have furnished interesting results. There seems to be much promise in further work along this two-stage methodology.

Towards a "Better" Estimate of α

However, as equation (5) shows, computation of A^S requires estimate of λ, which in turn depends on an estimated value of α. Table 1 already presents a set of estimates of α obtained from LSDV. We notice that these estimates come with considerable precision for both the time periods. However, in view of potential problems with LSDV estimation, we want to explore whether it is possible to get better estimates of α.

One option is to use the GMM-SYS estimator. As noticed earlier, this estimator has the desirable theoretical property of being robust to omitted variable bias discussed in Islam (1995) and endogeneity bias discussed in Caseli *et al.* (1996). As mentioned in Section 3, under this estimator the level version of the growth-convergence equation (given by equation (2)) is added to the differenced version (given by equation (7)). The instrument set for the t-th period now includes $(y_{i,t-1} - y_{i,t-2})$ and $(x_{i,t-1} - x_{i,t-2})$ (required to identify the level equations), in addition to $y_{i,t-s}$ and $x_{i,t-s}$ (with $s = 2, \ldots, T - 2$, where T is the total number of periods) required to identify the differenced equations. While the validity of the stipulated instruments for the differenced-equations depends on the lack of serial correlation in v_{it}, the validity of the stipulated instruments for the level equations in GMM-SYS depends in addition on the lagged differences being uncorrelated with the individual (country) effect μ_i. That is, in addition to

(18) $$E[(\mu_i + \nu_{it})\Delta y_{i,t-1}] = 0,$$

GMM-SYS needs to have

(19) $$E[(\mu_i + \nu_{it})\Delta x_{i,t-1}] = 0.$$

To understand what this requirement means in the context of our model, we may note that the variable x_{it} represents $[\log(s_{it}) - \log(n_{it} + g + \delta)]$, where s_{it} is the rate of investment (measured as a ratio to the GDP) and n_{it} is the rate of growth in the labor force. On the other hand, g and δ are the rate of technological progress and the rate of depreciation, respectively, both of which are assumed to be constant across countries and time and hence do not play much role in the estimation process. Therefore, $\Delta x_{i,t-1}$, given by

(20) $$\Delta x_{i,t-1} = [\log(s_{i,t-1}) - \log(s_{i,t-2})] - [\log(n_{i,t-1} + g + \delta) - \log(n_{i,t-2} + g + \delta)],$$

basically stands for the rate of change in investment rate and acceleration in the labor force growth rate. It is difficult to argue that these will not be correlated with the individual country effect term μ_i, which is very encompassing in its scope. As Mankiw, Romer, and Weil (1992) rightly note, it includes "not just technology but resource endowments, climate, institutions, and so on" (p. 6). Accordingly, μ_i is very likely to be correlated with $\Delta x_{i,t-1}$. This indicates that even if GMM-SYS estimator displays superior performance in other contexts, it may not prove

TABLE 2a

RESULTS FROM GMM-SYS ESTIMATION FOR THE INITIAL PERIOD

Estimated Values of Reduced Form Coefficients	One-step GMM-SYS	Two-step GMM-SYS
$\hat{\gamma}$	1.0160	1.0151
	(0.0143)	(0.1735)
$\hat{\beta}$	0.0965	0.0991
	(0.0867)	(0.0631)
Estimated values of the structural parameters		
$\hat{\gamma}$	–0.0032	–0.0030
	(0.0028)	(0.0342)
$\hat{\alpha}$	1.1986	1.1793
	(0.3927)	(2.4020)
Test of over-identifying restrictions		
Sample value of Sargan test statistic		42.67
5% critical value of χ^2_{16}		26.30
1% critical value of χ^2_{16}		32.00

TABLE 2b

RESULTS FROM GMM-SYS ESTIMATION FOR THE SUBSEQUENT PERIOD

Estimated Values of Reduced Form Coefficients	One-step GMM-SYS	Two-step GMM-SYS
$\hat{\gamma}$	0.9993	0.9995
	(0.0107)	(0.1888)
$\hat{\beta}$	0.1608	0.1526
	(0.0854)	(0.1021)
Estimated values of the structural parameters		
$\hat{\lambda}$	0.0001	0.0001
	(0.0021)	(0.0378)
$\hat{\alpha}$	0.9957	0.9968
	(0.0645)	(1.2296)
Test of over-identifying restrictions		
Sample value of Sargan test statistic		45.91
5% critical value of χ^2_{16}		26.30
1% critical value of χ^2_{16}		32.00

Note: GMM-SYS estimator adds the level equation (2) to the differenced equation (3) and uses both level and first differences of lagged variables as instruments.

that successful in estimation of the parameters of the growth-convergence equation.[16]

The results from GMM-SYS estimator are presented in Table 2. We see that for both sub-periods, estimated values of α prove to be close to one. This is theoretically not plausible. The two-step GMM-SYS estimates are very imprecise too. The values of the Sargan statistic for test of over-identifying restrictions for both sub-periods exceed the critical χ^2 values at both 5 and 1 percent significance level. Thus the assumption that lagged first differences of the variables are uncorrelated with the individual effect term is not sustained. This explains the anomalous

[16]In fact, Blundell and Bond note even in their own context potential problems with regard to the assumptions embodied in equation (19).

TABLE 3a

MINIMUM DISTANCE ESTIMATION OF α, THE CAPITAL SHARE (NOT CORRECTED FOR BIAS)

Time Period	Estimated Value of α	Standard Error of Estimate	Value of the MD-statistic
(1)	(2)	(3)	(4)
1960–75	0.2037	0.0524	1.3681
1975–90	0.3654	0.1236	2.6716

Note: The MD statistic has a chi-square distribution with six degrees of freedom. The critical values are 10.64, 12.59, and 16.81 for 10, 5, and 1 percent level of significance, respectively.

TABLE 3b

BIAS CORRECTION OF THE ESTIMATED VAULE OF α, THE CAPITAL SHARE

Estimator	Bias in the Estimate of γ (%)	Bias in the Estimate of β (%)	RMSE of Estimate of γ (%)	RMSE of Estimate of β (%)	Bias Corrected Value of α for 1960–75	Bias Corrected Value of α for 1975–90
(1)	(2)	(3)	(4)	(5)	(6)	(7)
MD	–6.67	–0.43	6.2	24.1	0.2289	0.3742
LSDV	–8.03	0.00	7.1	23.7	0.2110	0.3531

Notes: (1) The Bias and RMSE (Root Mean Square Error) values are obtained from Islam (2000). The values are for the NONOIL sample, which (except for some countries that did not have data for 1990) is also the sample considered in this paper. The Bias and RMSE values are averages over three different data generating mechanisms (DGM) considered for the error term, namely AR(1), MA(1), and UC (uncorrelated).

(2) The bias-corrected estimates of α are obtained by incorporating bias-corrected estimates of γ and β in the formula $\alpha = \beta/(1 - \gamma + \beta)$.

results. In view of the rejection of the identifying assumption, and the related theoretical implausibility of the obtained values, GMM-SYS estimates of the parameters are not deemed suitable for computation of productivity indices in this paper.

This brings us to the MD estimator, which as noticed in Section 3, has several attractive properties. Results from the MD estimator are presented in Table 3a. As we can see, the MD estimates are close in value to the LSDV estimates presented in Table 1. While this similarity of estimates obtained from different estimators is reassuring, we need to assess these estimates in the light of possible small sample and endogeneity biases discussed in Section 3. In order to do so, we use Monte Carlo results on the performance of these estimators presented in Islam (2000). These Monte Carlo experiments were performed on the basis of the actual PWT data that are used for estimation in this paper too. Hence biases obtained from these experiments embody both small sample bias and potential endogeneity bias.

Table 3b reproduces the bias results for estimates of γ and β obtained in Islam (2000). The numbers are for the NONOIL sample, because this is also the sample that is studied in this paper.[17] The bias and RMSE (Root Mean Sum of Squares) figures presented in the table are averages over three different possible

[17]Except for a few countries that do not have data for 1990.

data generation mechanisms for the error term considered in that study, namely AR(1), MA(1), and UC.[18] Note that the bias results are not directly for α. They are rather for γ and β. However, we can obtain bias-corrected values of α by incorporating bias corrected values of γ and β into the formula: $\alpha = \beta/(1 - \gamma + \beta)$. Columns (6) and (7) of Table 3b present the bias corrected values α for the initial 1960–75 and subsequent 1975–90 periods, respectively. The corrections do change the estimates somewhat, though not to a great extent.

Given the relatively better performance of both MD and LSDV, we may want to use bias corrected estimates obtained from both these estimators in order to arrive at overall estimates. We can do so by taking weighted averages of MD and LSDV estimates using respective RMSE values as weights. The resulting estimate of α from this procedure turns out to be 0.2199 for the initial period and 0.3636 for the later period.

Of note here is the considerable increase in the value of α for the subsequent period compared with that for the initial period. Two factors might have contributed to this outcome. First, as we know, α here represents the exponent of capital in equation (2), which does not include "human capital" as a separate input. The labor input variable L is measured by number of people (workers). Hence human capital cannot enter the picture through L. Yet development of human capital often requires some physical capital (in the form of school buildings, for example). It is therefore possible that some of the increased importance of human capital in the production processes of the more recent period (compared to those of the earlier period) found its expression in the larger coefficient for physical capital, K. The second possible reason for a higher value of α in the more recent period concerns distribution. It is widely recognized that the balance of social forces has moved more in favor of owners of capital in the 1980s compared with that in the 1970s. Waning strength of labor unions, rising inequality in income and wealth, etc. are some reflections of this process. These distributional changes together with increased importance of human capital can probably explain the notable increase in the value of the capital share parameter.

Despite the care taken in arriving at α values to be used for computation of productivity indices, it is not the claim here that we have found the best estimates, and that there is no room for further improvement. However, compared to the alternative of imposing values of α arbitrarily, we at least allow data to play a role in determining these values. This has not been inconsequential. As we can see, the estimated values of α for the two periods differ considerably. This is something that we probably would have missed if we assumed values of α arbitrarily. We now turn to the task of computation of productivity indices using the parameter estimates.

5. Productivity Levels and Changes

The estimated coefficients of the dynamic model (equation (1)) can be used to obtain the estimated values of μ_i. The correspondence given by equations (3)

[18]These stand for Autoregressive process of order one, Moving Average process of order one, and Uncorrelated, respectively.

TABLE 4

BEST AND WORST TFP PERFORMERS

Rank	Top Ten in the Initial Period	Top Ten in the Subsequent Period	Rank	Bottom Ten in the Initial Period	Bottom Ten in the Subsequent Period
1	U.S.	U.S.	83	Mali	Togo
2	Switzerland	Hong Kong	82	Malawi	Malawi
3	Canada	Canada	81	Burundi	Mauritania
4	Sweden	Sweden	80	Togo	Burundi
5	Australia	Australia	79	Kenya	Zambia
6	New Zealand	Switzerland	78	Ctrl. Afr. Rep.	Mali
7	Denmark	U.K.	77	India	Kenya
8	Trinidad	Iceland	76	Rwanda	Ctrl. Afr. Rep.
9	Netherlands	Norway	75	Mauritania	Chad
10	France	Denmark	74	Uganda	India

Notes: (1) The ranks are on the basis of estimated values of μ_i from the model:

$$y_{it} = \gamma\, y_{i,t-1} + \beta x_{i,t-1} + \mu_i + \eta_t + \nu_{it}.$$

This is equation (2) in the text, which explains the notations. The productivity levels are recovered using the relationship $\mu_i = (1 - e^{-\gamma\tau})\ln A_{0i}$.

(2) The "Initial Period" refers to 1960–75, and the "Subsequent Period" refers to 1975–90.

and (5) can then be used to recover the estimated values of A_{0i}. Appendix Table A1 compiles the results. Columns (2)–(4) of this table show results on relative productivity levels for the initial period, and columns (5)–(7) show the results for the subsequent period. The numbers in columns (8) and (9) give ordinal and cardinal measures of change in productivity level of individual countries between the two periods.

To help assimilate the information provided in Table A1, we present several simpler tables. Table 4 shows the top-ten and the bottom-ten countries in terms of total factor productivity in the two sub-periods. Several things come to notice. The first is persistence. We see that six countries appear in the top-ten list of both periods. These countries are the U.S., Switzerland, Canada, Sweden, Australia, and Denmark. Some of these countries even retain their exact rank. Thus the U.S., Canada, Sweden, and Australia retain their first, third, fourth, and fifth rank, respectively, in both periods. The notable addition to the top-ten list of the subsequent period is Hong Kong, which now occupies the second place. The U.K., Norway, and Iceland are other additions. The countries that lose their place in the top-ten list are New Zealand, Trinidad, the Netherlands, and France. Of these the latter three were already in the lower rung of the initial period's top-ten list.

The persistence is even more pronounced for the bottom-ten list. As we can see from Table 4, eight countries of the bottom-ten list of the initial period continue to be in this list for the subsequent period. Only two countries, namely Uganda and Rwanda, lift themselves to higher productivity levels in the subsequent period, and Chad and Zambia replace them in the bottom-ten list.

Most of the high-productivity countries are, not surprisingly, from North America and Europe. Interestingly Japan is not to be found among the top-ten, either in the initial or in the later period. However, as already noted, Hong Kong

TABLE 5

PRODUCTIVITY DYNAMICS: CHANGE OF RANK

Improvement in Rank by	No. of Countries	Countries	Deterioration in rank by	No. of Countries	Countries
1–5	18	Germany, Ghana, Burundi, Kenya, Japan, Ctrl. Afr. Rep., Honduras, Brazil, Colombia, India, Bolivia, Italy, U.K., Paraguay, Morocco, Portugal. Mauritius, Mali	1–5	16	Dom. Rep., Philippines, Zimbabwe, Switzerland, France, Denmark, Madagascar, Chad, Togo, Chile, Ecuador, Spain, Finland, Algeria, Netherlands, Austria
6–10	10	Uganda, Norway, Rwanda, Singapore, Pakistan, Cameroon, Senegal, Sri Lanka, Iceland, Malaysia	6–10	10	Benin, Zambia, Guatemala, Costa Rica, Panama, Trinidad, Mauritania, Argentina, Uruguay. Turkey
11–15	0		11–15	5	New Zealand, Venezuela, El Salvador, Mozambique, South Africa
16–20	6	Egypt, Tunisia, Thailand, Congo, Bangladesh, Korea	16–20	3	Papua New Guinea, Jamaica, Ivory Coast
More than 20	2	Hong Kong, Jordan	More than 20	2	Peru, Nicaragua

Notes: (1) The ranks are on the basis of estimated values of μ_i from the model:

$$y_{it} = \gamma\, y_{i,t-1} + \beta x_{i,t-1} + \mu_i + \eta_t + \nu_{it}.$$

This is equation (2) in the text, which explains the notations. The productivity levels are recovered using the relationship $\gamma_i = (1 - e^{-\gamma\tau})\ln A_{0i}$.

(2) The changes (improvement and deterioration) in rank are between the Initial Period of 1960–75 and the Subsequent Period of 1975–90.

enters the top-ten list of the later period. On the other hand, most of the low productivity countries are, again not surprisingly, from sub-Saharan Africa. The only exception is India. Despite her high investment rates, India finds herself in the bottom rung of productivity in both the periods.

The persistence of countries in the top and the bottom list however should not overshadow the wide-ranging movements that occur between the two periods. One can look at these dynamics from two viewpoints, namely the ordinal and cardinal. The ordinal view is presented in Table 5. It summarizes the extent of movements in terms of change in rank.

Table 5 leads to the following observations. First, we see that there are roughly as many countries that experience improvement in their productivity rank as experience deterioration. Second, there are 11 countries whose ranks do not change at all. These are Australia (5), Belgium (14), Canada (3), Greece (27), Israel

(21), Mexico (25), Malawi (82), Nigeria (73), Syria (30), Sweden (4), and the U.S. (1). As their ranks (reported in parentheses) indicate, these countries are fairly spread across the distribution. Second, most of the changes in rank are of limited extent. Thus we see that for 18 (of 36) countries, the improvement in rank remains limited to the 1–5 range. For another ten, rank improvements range between 6 and 10. The picture is similar on the deterioration side. For 16 (out of 36) countries, the deterioration in rank remains limited to the 1–5 range. For another ten the rank deterioration ranges between 6 and 10. Among countries that experience large improvements in rank are Hong Kong and Jordan. The countries that witness severe rank deterioration include Nicaragua and Peru. Of note is that sub-Saharan African countries are not among the ones that undergo large rank deterioration. This is because most of these countries were already in the lower productivity rung. Productivity turbulence seems to be more prominent among non-African countries.

While ordinal dynamics of productivity (in the form of rank changes) are informative, more useful for subsequent analysis are cardinal shifts in productivity. For such a cardinal analysis we express productivity levels of individual countries as percentage of the U.S. productivity level in both periods. The fact that the U.S. ranks the highest in the productivity scale for both periods makes such a procedure more appealing. The numbers in column (4) show the productivity level of a country relative to that of the U.S. in the initial period. The numbers in column (7) show the same for the subsequent period. The numbers in column (9) are differences between column (7) and (4) and thus give the change (in percentage points) in the relative productivity level between the two periods (with the U.S. as the common benchmark). Table 6 provides a summary version of this information.

The first thing that we may notice from this table is that countries witnessing improvement in their relative (to the U.S.) productivity level far outnumber countries that witness deterioration. While 72 countries belong to the former category, only nine belong to the latter. This may be encouraging and be taken as a sign of technological diffusion. Unfortunately the improvements in most cases are of very small magnitude. As Table 6 shows, for 19 of these countries the improvement was only up to five percentage points. For another 26, the improvements ranged between five and ten percentage points. Thus, despite some improvements in their relative productivity level, most of the countries remain piled up at the bottom end of the productivity scale. However, some countries did experience improvements in relative productivity level, ranging more than 20 percentage points. These include Asian Tigers such as Hong Kong, Singapore, and Korea, suggesting that alongside accumulation, productivity growth also played an important role in the recent growth of these countries. Jordan, Mauritius, and Iceland also belong to this group. On the other hand, about ten countries saw their relative productivity level decrease. Many of these countries are from Latin America. But they also include some high productivity level countries such as Australia, New Zealand, Sweden, and Switzerland, which saw their productivity level slipping down relative to that of the U.S.

The results of ordinal and cardinal changes in productivity described above can be presented in the form of a graph as in Figure 1.

TABLE 6

PRODUCTIVITY DYNAMICS: CHANGE IN RELATIVE PRODUCTIVITY

Improvement in Relative pdvty by (pct. points)	No. of Countries	Countries	Deterioration in Relative pdvty by (pct. points)	No. of Countries	Countries
0–5	19	Mauritania, Zambia, Jamaica, Uruguay, Ivory Coast, South Africa, Trinidad, Benin, Togo, Mozambique, El Salvador, Spain, France, Philippines, Costa Rica, Netherlands, Malawi, Chad, Denmark	0–5	4	Peru, Sweden, Australia, Papua New Guinea
6–10	26	Zimbabwe, Burundi, Nigeria, Dom. Rep., Mali, Ctrl. Aft. Rep., Kenya, Canada, Honduras, Germany, India, Madagascar, Panama, Guatemala, Turkey, Algeria, Uganda, Ghana, Ecuador, Rwanda, Chile, Belgium, Austria, Bolivia, Paraguay, Finland	6–10	3	New Zealand, Nicaragua, Argentina
11–15	14	Cameroon, Israel, U.K., Pakistan, Senegal, Sri Lanka, Morocco, Greece, Colombia, Mexico, Brazil, Syria, Japan, Italy	11–15	1	Switzerland
16–20	7	Norway, Thailand, Bangladesh, Egypt, Tunisia, Malaysia, Portugal	16–20	1	Venezuela
More than 20	7	Singapore, Hong Kong, Korea, Iceland, Jordan, Congo, Mauritius	More than 20	0	

Notes: (1) Relative productivity level signifies the ratio of A_0 of a country to A_0 of the U.S. for the same period.

(2) The changes (improvement and deterioration) in rank are between the Initial Period of 1960–75 and the Subsequent Period of 1975–90.

The x-axis represents the relative (to the U.S.) productivity level in the initial period. The y-axis does the same for the subsequent period. The 45-degree line represents points where relative levels in the two periods are the same. All observations made on the basis of Tables 4–6 can now be perused in the context of this graph. For example, we notice that most of the countries are above the 45-degree

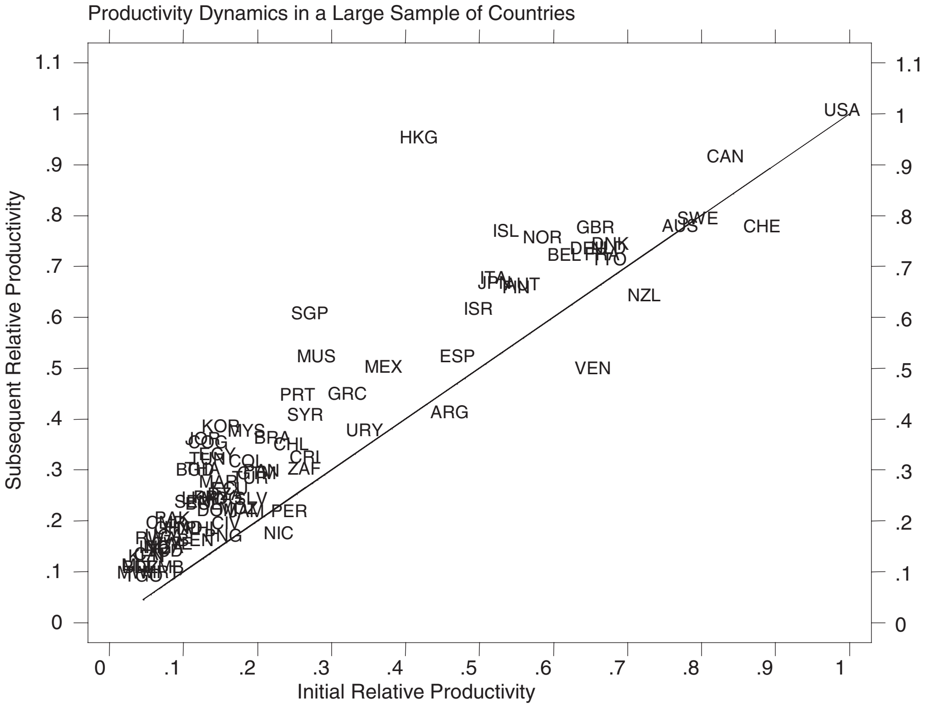

Figure 1. Productivity Dynamics in a Large Sample of Countries

Note: "Initial Relative Productivity" refers to productivity relative to the U.S. during 1960–75, and "Subsequent Relative Productivity" refers to productivity relative to the U.S. during 1975–90. 1980s. Relative productivity is measured by the ratio $\frac{A_{0i}}{A_{0,US}}$. The data for the graph are given in columns (4) and (7) of Table A1.

line, reflecting the improvement in their relative productivity level. At the same time, we note the piling up of countries at the lower end of the productivity scale, illustrating graphically the fact that despite some improvement in their relative productivity level, a vast number of countries still remain far removed from the productivity levels of the leading countries. The graph also shows the outstanding productivity performance of Hong Kong. From 42 percent in the initial period, Hong Kong's relative productivity level in the subsequent period has risen to 95 percent, bringing it very close to that of the U.S. The graph also shows other countries of the positive productivity performance envelope. These include Canada, Iceland, Singapore, and Korea. The graph also displays the envelope of negative productivity performance. As noted earlier, most of these are Latin American countries such as Venezuela, Argentina, Peru, and Nicaragua.

6. Conclusions

The paper computes and reveals the nature of productivity dynamics in a large sample of countries. Recent research has shown that productivity differences far overshadow differences in capital accumulation in accounting for (per capita) income differences across countries. However, analysis of international productivity differences has not kept up with this importance. For a long time, cross-country growth regularities were studied under the assumption of identical technology for all countries. Recent research has broken that mold, and this has led to some attention being given to productivity differences across countries. The rise of new methodologies for estimation of productivity indices in large samples of countries is also associated with this paradigm shift. However, until now these methodologies produced mainly one-shot pictures of productivity differences across countries. In this paper, we compute productivity indices for two different time periods and thus present a picture of productivity *dynamics*.

The picture obtained is complex. First, we see that a large number of countries experience some improvement in their relative productivity level *vis-à-vis* the leading country, the U.S. This is encouraging and can be interpreted as a sign of technological diffusion. Second, the magnitude of these improvements is however so small that bulk of the countries still remain far removed from the productivity level of the U.S. Third, there are countries that in contrast to those remaining, experience such large improvements in relative productivity level that bring them closer to the leading countries. Fourth, there are a considerate number of countries that experience deterioration in their relative productivity level. Finally, all these movements of different magnitudes and directions result in considerable turbulence in the productivity ranking. We find that there are as many countries (36) experiencing improvement in productivity rank as witnessing deterioration.

Of course, results presented in this paper need to be viewed with some caution. First, there are issues regarding the PWT data used in this paper. Relative productivity indices cannot be computed unless data for different countries are brought to a common base. From this point of view, PWT is appealing because it has a common base, and the conversion has been done using the purchasing power parity (PPP) principle. Also, most of the recent papers on growth and productivity have used this data set.[19] However there are researchers who have expressed doubt about the validity of the PWT data and have questioned the merit of research done on their basis.[20] While we do not share the extreme variants of this criticism, we recognize that certain aspects of the results presented in this paper may actually be due to data construction rather than to the genuine economic processes of interest.

Second, there are some issues with regard to the methodology. The paper makes an effort to get satisfactory estimates of α in a data-dependent way, instead of assuming these values arbitrarily. However, there may be scope for further improvement in the econometric procedures used. More importantly, one may still remain squeamish about the assumption of a common value of α for all countries of the sample. Efforts to relax this restriction may continue even though it is

[19]The American Economic Association (AEA) has even awarded prize to Robert Summers and Alan Heston for putting together this data set.

[20]See for example Bardhan (1995). Temple (1998) also discusses the data issues.

difficult to either obtain or econometrically estimate country-specific values of α, particularly for different periods.[21]

Despite these qualifications, what remains true is that productivity dynamics differ enormously across countries. The intriguing question is what determines the direction and magnitude of these dynamics. The information on productivity dynamics produced by this paper can provide a useful point of departure for a second-stage analysis geared toward finding the determinants of productivity. As is known, A_{0i} and TFP is an omnibus term that has many different components. In his Nobel address, Solow (1988) approvingly mentions "unpacking" by Denison of "technological progress in the broadest sense" into "technological progress in the narrow sense" and other constituent elements. Thus there is already a tradition of analysis proceeding from initial computation of productivity indices. This tradition can now be extended to yield a two-stage analysis, the second stage of which can be conducted using the regression framework. The intriguing question of the exact way in which human capital influences growth can also be better examined following such a two-stage analysis. Improving further the methodology of productivity index computation and pursuing a second-stage analysis of these indices to identify determinants of productivity are the two lines in which future research on this topic can fruitfully proceed.

Finally, the analysis on the basis of large sample needs to be complemented by analyses focused on particular sub-groups or regions of countries. Such narrowly focused analysis may also be helpful in identifying the pitfalls in the data covering large samples.

[21]A similar issue concerns g. This paper continues with the assumption of a common g *within* a period. This allows treating the ratio of initial productivity level as the relative productivity level for the period as a whole. This can be illustrated through equation below.

$$\frac{A_{it}}{A_{jt}} = \frac{A_{0i}e^{gt}}{A_{0j}e^{gt}} = \frac{A_{0i}}{A_{0j}}.$$

However, this also leaves unexplained what leads to change in the relative productivity level from one period to the other. The assumption of a within-period common g thus has a contradiction with substantial *between* period changes in relative productivity level that this study reveals. This is another issue on which future research may focus.

TABLE A1

PRODUCTIVITY DYNAMICS IN A LARGE SAMPLE OF COUNTRIES

Country	Initial $(\mu_i - \overline{\mu})$	Initial Productivity Rank	Initial Productivity Relative to the U.S.	Subsequent $(\mu_i - \overline{\mu})$	Subsequent Productivity Rank	Subsequent Productivity Relative to the U.S.	Change in Productivity Rank	Change in Relative (to the U.S.) Productivity
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Argentina	0.4567	23	0.4698	0.1580	29	0.4059	–6	–0.0639
Australia	0.7629	5	0.7809	0.5460	5	0.7727	0	–0.0082
Austria	0.5707	16	0.5677	0.4485	18	0.6572	–2	0.0896
Burundi	–0.9388	81	0.0464	–0.6821	80	0.1007	1	0.0543
Belgium	0.6288	14	0.6250	0.4987	14	0.7144	0	0.0894
Benin	–0.3341	63	0.1265	–0.4248	71	0.1543	–8	0.0278
Bangladesh	–0.3356	64	0.1261	–0.0403	44	0.2920	20	0.1659
Bolivia	–0.2896	59	0.1361	–0.1938	56	0.2264	3	0.0902
Brazil	0.0268	37	0.2302	0.0765	34	0.3545	3	0.1243
Ctrl. Afr. Rep.	–0.7131	78	0.0674	–0.5394	76	0.1276	2	0.0602
Canada	0.8092	3	0.8432	0.6434	3	0.9084	0	0.0651
Switzerland	0.8433	2	0.8923	0.5451	6	0.7716	–4	–0.1207
Chile	0.0892	34	0.2553	0.0568	37	0.3431	–3	0.0879
Cost de Ivory	–0.1662	47	0.1671	–0.3083	63	0.1872	–16	0.0201
Cameroon	–0.5575	70	0.0873	–0.3057	62	0.1880	8	0.1007
Congo	–0.2565	56	0.1438	0.0628	36	0.3466	20	0.2027
Colombia	–0.0717	44	0.1955	–0.0078	41	0.3083	3	0.1128
Costa Rica	0.1305	32	0.2734	0.0092	39	0.3170	–7	0.0437
Germany	0.6595	13	0.6577	0.5098	12	0.7277	1	0.0700
Denmark	0.6862	7	0.6875	0.5174	10	0.7369	–3	0.0494
Dom. Rep.	–0.2058	53	0.1565	–0.2300	58	0.2132	–5	0.0567
Algeria	–0.1692	48	0.1663	–0.1500	50	0.2435	–2	0.0772
Ecuador	–0.1445	46	0.1732	–0.1200	49	0.2559	–3	0.0827
Egypt	–0.2110	54	0.1551	0.0211	38	0.3234	16	0.1683
Spain	0.4701	22	0.4803	0.3016	24	0.5151	–2	0.0348
Finland	0.5617	17	0.5592	0.4423	19	0.6506	–2	0.0914
France	0.6758	10	0.6758	0.4995	13	0.7154	–3	0.0395
UK	0.6679	11	0.6670	0.5428	7	0.7687	4	0.1017
Ghana	–0.4949	67	0.0968	–0.33956	66	0.1777	1	0.0809
Greece	0.2470	27	0.3317	0.2103	27	0.4426	0	0.1109
Guatemala	–0.0315	39	0.2090	–0.0531	46	0.2859	–7	0.0770
Hong Kong	0.4015	24	0.4287	0.6679	2	0.9461	22	0.5174
Honduras	–0.4167	66	0.1103	–0.3342	64	0.1793	2	0.0691
India	–0.6940	77	0.0696	–0.4840	74	0.1399	3	0.0703
Iceland	0.5453	18	0.5442	0.5372	8	0.7616	10	0.2174
Israel	0.5039	21	0.5080	0.4024	21	0.6089	0	0.1009
Italy	0.5278	20	0.5286	0.4600	16	0.6699	4	0.1413
Jamaica	–0.0706	42	0.1958	–0.2352	59	0.2113	–17	0.0155
Jordan	–0.2883	58	0.1364	0.0743	35	0.3532	23	0.2168
Japan	0.5299	19	0.5304	0.4516	17	0.6607	2	0.1303
Kenya	–0.7848	79	0.0599	–0.5642	77	0.1224	2	0.0626
Korea	–0.1883	51	0.1611	0.1160	31	0.3786	20	0.2175
Sri Lanka	–0.3191	62	0.1296	–0.1654	52	0.2373	10	0.1077
Morocco	–0.2001	52	0.1580	–0.0914	48	0.2683	4	0.1104
Madagascar	–0.1849	50	0.1620	–0.1661	53	0.2370	–3	0.0750
Mexico	0.3304	25	0.3809	0.2771	25	0.4946	0	0.1137
Mali	–0.9546	83	0.0452	–0.6591	78	0.1046	5	0.0594
Mozambique	–0.1053	45	0.1849	–0.2110	57	0.2164	–12	0.0315
Mauritania	–0.6075	75	0.0803	–0.7344	81	0.0923	–6	0.0120
Mauritius	0.1666	28	0.2903	0.3024	23	0.5157	5	0.2255
Malawi	–0.9452	82	0.0459	–0.7465	82	0.0905	0	0.0446
Malaysia	–0.0717	43	0.1955	0.1006	33	0.3690	10	0.1735
Nigeria	–0.5793	73	0.0842	–0.4816	73	0.1404	0	0.0562
Nicaragua	0.0491	36	0.2388	–0.3702	67	0.1689	–31	–0.0699
Netherlands	0.6837	9	0.6847	0.5109	11	0.7290	–2	0.0444
Norway	0.5995	15	0.5954	0.5274	9	0.7492	6	0.1538
New Zealand	0.7248	6	0.7330	0.4278	20	0.6351	–14	–0.0980
Pakistan	–0.5090	69	0.0946	–0.2752	61	0.1978	8	0.1032
Panama	–0.0124	38	0.2157	–0.0428	45	0.2908	–7	0.0752
Peru	0.0833	35	0.2528	–0.2365	60	0.2109	–25	–0.0419
Philippines	–0.2960	61	0.1347	–0.3382	65	0.1781	–4	0.0435

TABLE A1 (*continued*)

Country	Initial $(\mu_i - \bar{\mu})$	Initial Productivity Rank	Initial Productivity Relative to the U.S.	Subsequent $(\mu_i - \bar{\mu})$	Subsequent Productivity Rank	Subsequent Productivity Relative to the U.S.	Change in Productivity Rank	Change in Relative (to the U.S.) Productivity
P. N. Guinea	–0.1770	49	0.1641	–0.3947	69	0.1622	–20	–0.0019
Portugal	0.1111	33	0.2647	0.2058	28	0.4394	5	0.1746
Paraguay	–0.2409	55	0.1476	–0.1629	51	0.2383	4	0.0907
Rwanda	–0.6571	76	0.0740	–0.4056	70	0.1593	6	0.0853
Senegal	–0.3512	65	0.1229	–0.1856	55	0.2295	10	0.1066
Singapore	0.1456	29	0.2803	0.3939	22	0.6004	7	0.3200
El Salvador	–0.0545	40	0.2011	–0.1691	54	0.2359	–14	0.0347
Sweden	0.7819	4	0.8059	0.5569	4	0.7868	0	–0.0191
Syria	0.1328	30	0.2744	0.1500	30	0.4005	0	0.1261
Chad	–0.5726	72	0.0851	–0.5145	75	0.1329	–3	0.0478
Togo	–0.8285	80	0.0557	–0.7884	83	0.0844	–3	0.0287
Thailand	–0.2914	60	0.1357	–0.0346	42	0.2948	18	0.1591
Trinidad	0.6838	8	0.6848	0.4922	15	0.7067	–7	0.0220
Tunisia	–0.2610	57	0.1428	0.0037	40	0.3142	17	0.1714
Turkey	–0.0577	41	0.2000	–0.0718	47	0.2772	–6	0.0771
Uganda	–0.5806	74	0.0840	–0.3943	68	0.1623	6	0.0783
Uruguay	0.2876	26	0.3458	0.1029	32	0.3704	–6	0.0156
U.S.	0.9119	1	1.0000	0.7014	1	1.0000	0	1.0000
Venezuela	0.6647	12	0.6635	0.2737	26	0.4918	–14	–0.1717
South Africa	0.1313	31	0.2738	–0.0351	43	0.2946	–12	0.0208
Zambia	–0.5606	71	0.0868	–0.6763	79	0.1016	–8	0.0148
Zimbabwe	–0.5018	68	0.0957	–0.4525	72	0.1474	–4	0.0516

Note: The μ_i's are the estimated country effects obtained from estimation of equation (1). As equation (5) shows: $\mu_i = (1 - e^{-\lambda\tau})\ln A_{0i}$. The $\bar{\mu}$ is the average of μ_i over i, where i is the subscript for the countries.

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