International TFP dynamics and human capital stocks: a panel data analysis, 1960-2003

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Abstract

This paper adopts a fixed-effect panel methodology that enables us to take into account both TFP and neoclassical convergence. We use a sample of 76 countries, 1960-2003 and estimate TFP values obtained by using different estimators such as LSDV, Kiviet-corrected LSDV, and GMM *à la* Arellano and Bond. In our estimates, cross-country TFP dynamics shows that most countries in the sample do not catch up with the USA. We also find conditional convergence in TFP levels and that human capital acts as a robust enhancing factor of technology adoption, as suggested by Nelson and Phelps in 1966. In contrast with previous evidence, in our results even very low level of human capital stocks allow a country to enter a "conditional TFP convergence club" – a result again consistent with the original version of the Nelson-Phelps hypothesis. Further, our results imply a plausible link between stages of development and returns to different levels of education. Finally, the positive influence of human capital on technology catch up is robust to the inclusion of controls for a country's institutional quality.

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1. Introduction

A large body of empirical evidence on cross-country economic growth reveals that *per capita* income tends to converge to country-specific steady-states, and that *sigma*-convergence is generally absent. In other words, the world income distribution does not become less dispersed over time, with poor countries on average failing to grow faster than the rich ones [Pritchett (1997), Durlauf *et al.* (2005) and Grier *et al.* (2007)]. Another robust empirical result is that the large gaps in cross-country *per capita* income are mostly accounted for by differences in total factor productivity (TFP), rather than in factors of production [Klenow and Rodriguez-Clare (1997), Hall and Jones (1999)].[1]

The coexistence of a weak process of absolute convergence and of large TFP differentials poses an interesting question. In theory, the large differences in the estimated TFP levels are a potential source of flows of technology from advanced to less developed countries and, therefore, of income convergence. However, the very weakness of global convergence suggests the possibility that for many lagging countries this lever is not as simple to use as a number of models would postulate.[2] This difficulty might be due to their human capital stocks being too low, as firstly suggested by Nelson and Phelps (1966), or to the lacking quality of their institutions, as in Hall and Jones (1999) and in Acemoglu *et al.* (2001), or to the existence of monopoly rights of various forms that create a barrier to technology adoption, as in Parente and Prescott (1999).

In this paper we address two main questions. First, is convergence weak because technology catch-up is weak, in spite of the large differentials in technology? Second, if technology diffusion fails to materialize in many countries, what are the reasons for this failure? In particular, how important is human capital in favouring cross-country diffusion of technology?

These are old standing important questions. As maintained more than ten years ago by Bernard and Jones (1996), these questions call for direct analysis of the evolution of cross-country TFP levels over time.[3] A decade later, only partial answers are available. One possible reason for this is that estimating TFP levels and identifying the role of technology diffusion within income convergence is not simple. Existing empirical analyses confirm this difficulty: a number of different methodologies have been adopted, none of which has emerged as a recognized standard, and the evidence produced so far is not uniform. As section 2 below documents in details, the available evidence ranges from supporting strong conditional convergence in TFP levels to suggesting that the observed cross-country TFP dynamics is mostly due to random shocks.

[1] On the role of TFP heterogeneity in cross-country analysis see also in Parente and Prescott (1999), Easterly and Levine (2001), and Lucas (2000) among the many others. Few economists dispute these findings. Among them see Young (1994) and, more recently, Baier *et al.* (2002).

[2] For instance, in Mankiw, Romer and Weil (1992) technology diffusion is instantaneous and complete, so that differences in TFP levels across countries are a purely random phenomenon.

[3] As Bernard and Jones (1996, p. 1043) put it, "Why do countries have different levels of technology? How do technologies change over time?". Until these questions are not answered, they add, we do not know "how much of the convergence that we observe is due to convergence in technology versus convergence in capital-labour ratios".

To help clarify the matter, our first step is to adopt a methodology that allows us to estimate TFP at different points in time. Our choice builds on Islam (2003a), in which the presence of TFP heterogeneity in cross-country convergence analysis is tested by using a fixed-effects panel estimator in a standard convergence equation framework. It has been shown that this framework can be used to examine cases in which TFP differences in levels are not constants and, therefore, to test for the presence of TFP convergence. The main feature of this framework is that TFP levels are estimated by means of growth regressions in which the contribution of factor accumulation – namely, capital deepening – to income convergence is taken into account. By doing this, we limit the risk of overstating the role of TFP dynamics within that process.[4]

The robustness of our results is assessed by comparing the estimates obtained by using different estimators, namely, OLS, a Least Square with Dummy Variable (LSDV) estimator, a biased-corrected LSDV estimator (Kiviet, 1995) and a GMM (Arellano-Bond, 1991) estimator. We use a procedure suggested by Bond *et al.* (2001) and Monte Carlo results to select plausible estimates.

We use data on GDP per capita of 76 countries, both developed and less developed, over the period 1960-2003.[5] It is worth underlining that this time span includes the Nineties, a decade characterized by the IT revolution, a phenomenon known to be the source of a significant asymmetric shock on cross-country productivity levels, with the USA and the more developed economies as the major beneficiaries.[6] Our data are mainly from the *Penn World Tables* (2006) with the exception of human capital data, which are from Barro and Lee (2000),[7] and of indexes of institutional quality, which are based on data from the *International Risk Guide* and on openness to trade from Sachs and Warner (1995).[8]

Our results confirm that cross-country gaps in TFP levels are wide, that they are persistent, and that they are an important component of GDP per capita dynamics. In particular, we find an absence of TFP convergence in a period in which the same phenomenon characterises cross-country GDP per capita. The persistence of TFP differentials is strongly confirmed by the analysis of the shape of the whole cross-country distribution, which remains almost identical across periods. The link between TFP and GDP cross-country performances in time is further supported by the strong correlation existing between changes in TFP and GDP rankings. Concerning individual country's

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[4] More generally, this methodology offers various advantages with respect to existing alternatives. In particular, it neither call for the imposition of too many assumptions nor it requires the use of large datasets. These problems may be present, for instance, with techniques such as growth/level accounting and DEA. See section 2 below and Di Liberto *et al.* (2008) for more details.
[5] The time span in our paper is significantly longer than those used by most of the other available papers on TFP dynamics. Typically, they do not extend the analysis beyond 1990. See section 2 below.
[6] See Jorgenson (2005).
[7] The sample of 76 countries is the largest obtainable with these datasets: version 6.2 of Heston *et al.* (2006), and Barro Lee (2000), human capital updated files.
[8] See section 6 below for further details.

performances, our analysis shows that in recent years the USA have consolidated their long-standing leadership in cross-country TFP levels.

In relation to why cross-country TFP gaps tend to be persistent, we produce new evidence strongly supporting one of the most influential hypothesis on technology convergence, due to Nelson and Phelps (1966) and based on the idea that a lagging country's capability to absorb technology from abroad is proportional to its technology gap and to its stock of human capital (see also Benhabib and Spiegel, 1994). In particular, our evidence (i) detects a process of TFP convergence conditional to the stock of human capital in the population; (ii) shows that the role of human capital turns out to be robust to the inclusion of various and widely used indexes of social infrastructure and openness (iii) shows that even very low level of human capital stocks allow a country to enter a "conditional TFP convergence club". Point (ii) and (iii) in particular differ from previous results reported in the literature. Point (ii) is in contrast with the idea that "the determinants of social infrastructure affect [productivity] only through social infrastructure and not directly", as put forward by Hall and Jones (1999), while point (iii) challenges the idea that convergence is trigged only if a threshold level of human capital is reached [Benhabib and Spiegel, (2005)]. In our evidence this threshold is so low that it can be ignored, and this yields further support to the original version of the Nelson-Phelps hypothesis.

Finally, we decompose our total human capital proxy into its components of primary, secondary and tertiary education, and find that there is a plausible link between stages of development and returns to different levels of education as suggested by recent studies (Vandenbussche *et al.*, 2006).

The rest of the paper is organized as follows. In section 2 we review the main papers on cross-country TFP dynamics. In section 3 we describe our chosen methodology to estimate TFP levels at different point in time, while in section 4 we discuss how to select the estimator that suits our case better and presents our evidence on the degree of cross-country TFP heterogeneity. Section 5 shows how much TFP convergence can be detected in our dataset and section 6 tests if our TFP estimates are positively correlated with the observed human capital endowments. Finally, section 7 shows some evidence on the specific role on TFP growth played by different levels of education. Conclusions are in section 8.

2. Review of the literature

There exists a well known large body of empirical studies on convergence in which the assumption of cross-country TFP homogeneity is relaxed but no analysis of changes in TFP levels over time is offered.[9] In this section we focus exclusively on recent papers based on large samples of countries in which TFP dynamic patterns are addressed explicitly.[10]

As we have noticed in the Introduction, empirical results in this area are both far from uniform and difficult to compare. We start with those papers which claim that some cross-country TFP convergence is present and that some key determinants of the process can be identified.

Aiyar and Feyrer (2002) apply growth accounting techniques to estimate TFP levels for a sample of 86 countries for the period 1960-1990. The estimated TFP values are then used to perform a standard conditional convergence regression analysis. They use fixed-effects estimators to control for unobserved cross-country differences in geography and institutions. They find that technology catch-up is present in the form of conditional convergence in technology levels. About the determinants behind the process, they report that "the level of human capital has a positive effect on a country's ability to take advantage of technological spillovers", thus providing support to the Nelson and Phelps (1966) hypothesis. Another influential paper on the Nelson-Phelps hypothesis is Benhabib and Spiegel (2005)[11]. In this paper, they let human capital to be the source of "domestic innovation" as well as a determinant of technology adoption from abroad. TFP values are first estimated and then used as the dependent variable in growth regressions based on a sample of 75 countries over the 1960-95 period. The catch-up term turns out to be by far the major channel through which human capital enhances TFP growth in lagging countries. Another contribution of Benhabib and Spiegel (2005) is worth underlining – namely, their extension of the Nelson-Phelps approach to include the possibility that, unless a critical value of human capital stock is reached, the catch-up mechanism is not activated. In their evidence, this critical level does exist and turns out to be rather high, so that 27 countries out of 75 were below it in 1960.

Dowrick and Rogers (2002) study cross-country conditional convergence over the 1965-1990 period. Using country data on capital stocks and GDP per worker they model the rate of growth of the latter as a function of both "classical" and "technology" convergence. They too find that less developed countries benefit from technology transfer, and that secondary education strengthen the process. No explicit analysis of TFP dynamics is present in the paper: technology differentials are proxied by output per worker, a variable that can reflect many factors other than technology.[12]

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[9] Among the most influential see Islam (1995), Klenow and Rodriguez Clare (1997) and Hall and Jones (1999) that use a single TFP estimate.

[10] For a brief survey of previous studies on TFP convergence see Islam (2003b). These studies do not usually examine large samples of countries.

[11] In a previous 1994 paper, they find that the catch-up term is often a significant determinant of GDP growth, and that human capital exerts a much stronger influence on GDP growth through this channel rather than through the "domestic innovation" mechanism. This evidence is based on per capita GDP cross-country growth regressions for 78 countries over the 1965-85 period.

[12] The sample used in the paper is limited to 57 countries due to availability of data on capital stocks, and countries excluded from it are mainly developing countries.

Another paper that finds a positive role for TFP dynamics on GDP convergence is Wong (2007). Applying a yet different empirical methodology – namely, channel decomposition – to a sample of 77 countries from 1960 to 1985, Wong (2007) reports that while TFP growth is the main contributor to GDP per capita convergence, the contribution of human and physical capital are negligible. As in the previous study, no explicit analysis of cross-country TFP convergence and of its determinants is developed in the paper.[13]

Other papers are more doubtful about the strength of technological diffusion as a systematic source of income convergence. For example, Islam (2003a) finds "encouraging signs" that technological diffusion is taking place, although in a rather weak form. This is the paper closest to ours. Nevertheless, in Islam's paper, TFP estimates are not used for an econometric analysis of mechanisms of technology convergence/divergence, as it is done here. In his descriptive analysis based on a sample of 83 countries for the period 1960-90, Islam (2003a) finds some persistency in the estimated country rankings of relative TFP, with most countries nonetheless improving with respect to the USA (in our analysis, extended to include 2003, we find that the opposite is true).

Similarly to Dowrick and Rogers (2002), Kumar and Russell (2002) use data on physical capital stocks and therefore study technological convergence in a reduced sample of 57 countries between 1965 and 1990. They apply the Data Envelop Analysis (DEA) to decompose productivity growth into shifts of the world production frontier, technological catch-up, and capital-deepening, and find that "technological catch-up ... has done little, if anything, to lower income inequality across countries" (p. 537), because both richer and poorer countries seems to have benefited from the diffusion of technology. This result points to the possibilities that either the size of a poorer country's technology gap is not a determinant of the process of technology absorption from abroad, or that unfavourable differences in some conditioning factors (human capital, for instance) offset the positive role of that gap.

Finally, McQueen and Whelan (2007) use data on cross-country capital-output ratios to estimate the speed of convergence in a sample of 96 countries over the period 1960-2000. They detect a rather higher than usual speed of conditional convergence, and find that most of the cross-country variation in growth rates is due to variations in TFP. In their view, however, TFP variations are more likely to reflect random shocks *à la* Mankiw, Romer and Weil (1992) than patterns of systematic technology catch-up.[14]

[13] Another paper on TFP convergence is Miller and Upadhyay (2002), where absolute convergence in TFP is found in a sample of 83 countries for the period 1960-89. In this paper, however, the econometric problems of estimating a dynamic panel data model (see section 4 below) are not addressed.

[14] Similarly, Hausmann and Pritchett (2005) find that in a panel of 110 countries covering the 1957-1992 period, episodes of growth accelerations in GDP per capita are poorly predicted by standard growth determinants, and that they appear to be caused mostly by idiosyncratic changes.

3. A Panel Data approach to estimate TFP convergence

Our aim is to investigate cross-country TFP heterogeneity and convergence by using an appropriate fixed-effect panel estimator. Islam (1995) was among the first to suggest this econometric solution to the problem of allowing for TFP heterogeneity in convergence analysis.[15] In particular, he extended the standard Mankiw *et al.* (1992) structural approach by allowing TFP levels to vary across individual economies, together with saving rates and population growth rates. Unlike in the Mankiw *et al.* (1992) approach, Islam (1995) introduced the idea that the unobservable differences in TFP are correlated with other regressors, and uses suitable panel techniques to estimate:

$$y_{it} = \beta y_{it-\tau} + \sum_{j=1}^{2} \gamma_j x_{j,it} + \eta_t + \mu_i + v_{it} \qquad j=1,2 \qquad (1)$$

where the dependent variable is the logarithm of *per capita* GDP (measured in terms of population working age), v_{it} is the transitory term that varies across countries. The remaining terms are:

$$x_{1,it} = \ln(s_{it}) \qquad (2)$$

$$x_{2,it} = \ln(n_{it} + g + \delta) \qquad (3)$$

$$\gamma_1 = (1-\beta)\frac{\alpha}{1-\alpha} \qquad (4)$$

$$\gamma_2 = -(1-\beta)\frac{\alpha}{1-\alpha} \qquad (5)$$

$$\mu_i = (1-\beta)\ln A(0)_i \qquad (6)$$

$$\eta_t = g(t_2 - \beta t_1) \qquad (7)$$

where A_{i0} represents the initial level of technology, and s, n, δ are, respectively, the saving rate, the population growth rate, the depreciation rate; g is the exogenous rate of technological change,[16] assumed to be invariant across individual economies; α is the usual capital share of a standard Cobb-Douglas production function; finally, $\beta \equiv e^{-\lambda\tau}$, where $\lambda = (1-\alpha)(n+g+\delta)$ represents the convergence parameter and $\tau \equiv t_2 - t_1$ is the time span considered.

In this specification, technology is represented by two terms. The first term, μ_i, is a time-invariant component that varies across economies and should control for various unobservable factors. The second is the time trend component (eq. 7) that captures the growth rate of the technology frontier assumed constant across individuals. Once we have the estimated individual

[15] See also Caselli *et al.* (1996) and Islam (2003a) among others.

[16] As is standard in this literature, $(g+\delta)$ is assumed equal to 0.05.

intercepts, we can obtain an index of TFP by computing:

$$A(0)_i = \exp\left(\frac{\mu_i}{1-\beta}\right) \tag{8}$$

Since TFP estimates include all unobservable components assumed to be different across countries but constant over time such as technology gaps (more on this presently), culture and institutions, and since these components are likely to be correlated with other regressors, a fixed effect estimator is appropriate. If we apply LSDV to equation (1), individual effects may be directly estimated. With other estimators, such as Within Group or Arellano-Bond (1991), estimates of μ_i and, thus, of $\hat{A}(0)_i$ can be obtained through equation (1) by:[17]

$$(\hat{\mu}_i + \hat{u}_{it}) = y_{it} - \beta y_{it-\tau} - \sum_{j=1}^{2} \hat{\gamma}_j x_{j,it} \tag{9}$$

$$\hat{\hat{\mu}}_i = \frac{1}{T} \sum (\hat{\mu}_i + \hat{u}_{it}) \tag{10}$$

The main problem with this methodology is that, while it was designed to control for the presence of cross-country TFP heterogeneity, it rules out technology convergence by assumption. More precisely, equation (1) is obtained by log-linearizing the Solow model around the steady-state under the assumption of a stationary degree of TFP heterogeneity. In other words, technology in all economies is assumed to grow at the same rate whatever their position relative to the world frontier. This is in sharp contrast with the technological catch-up hypothesis. In the latter, a country's "technology gap" – if higher than its stationary value[18] – may enhance its TFP growth rate during the transition towards a steady state in which all economies will grow at the common rate g. As a consequence, a high degree of cross-country technology differentials is likely to be the source of TFP convergence.

Hence, how can we use equation (1) to test for the presence/absence of technological convergence? The solution is to estimate TFP values over several subsequent periods, in order to test whether the observed time pattern is consistent either with the catch-up hypothesis or with the alternative hypothesis that the current degree of technology heterogeneity is at its stationary value.[19]

More in details, differently from Islam (1995) we use PWT 6.2 data on GDP per worker

[17] See Caselli *et al.* (1996). We are excluding the time dummies since in our analysis data are transformed as in equation (12).
[18] In models of technology catch-up, stationary values of technology gaps are determined by differences in the countries' fundamentals. If the follower countries' gaps are beyond their stationary values, cross-country TFP dynamics should be characterized by a process of conditional convergence. More on this in section 6 below.
[19] Splitting a longer period in several subperiods has an additional advantage, since the longer the time dimension of the panel, the higher the risk that differences in TFP levels are not constant due to the presence of technological diffusion. In other words, equation (1) is likely to be an approximation of the real process – an approximation that deteriorates as the length of the period under analysis increases.

1960-2003 to estimate the following equation:

$$\tilde{y}_{it} = \beta\tilde{y}_{it-\tau} + \sum_{j=1}^{3} \gamma_j \tilde{x}_{j,it-\tau} + \mu_i + u_{it} \tag{11}$$

$$\tilde{y}_{it} = y_{it} - \overline{y}_t, \qquad \tilde{x}_{it} = x_{it} - \overline{x}_t \tag{12}$$

where $\overline{y}_t$ and $\overline{x}_t$ are the world averages in period t: data are taken in difference from the sample mean, in order to control for the presence of a time trend component η_t and of a likely common stochastic trend (the common component of technology) across countries.[20] We use a standard five-year time span in order to control for business cycle fluctuations and serial correlation, which are likely to affect the data in the short run. Moreover, we include the 2003 observation as our last observation in order to embrace the longest possible sample.[21] In terms of TFP convergence, these latter years are important in that developments in IT have been "… a rapidly rising source of aggregate productivity growth throughout the 1990's".[22] The additional regressor $x_{3,it}$ is an index of a country's stock of human capital based on the average years of schooling.[23] As we shall see, excluding human capital from the analysis does not change our results. All these variables are taken at their *t*-5 level to reduce endogeneity problems.

We improve on Islam (2003a) in three ways. First, Islam (2003a) estimates fixed effects, and thus TFP levels, using two estimators (the Minimum Distance, and system GMM) which, as we shall see below, do not represent an optimal choice in this context. Second, our period of analysis is significantly longer than his (i.e., 1960-1990), and therefore includes years strongly influenced by the introduction of IT technologies (more on this below). Third, Islam (2003a) suggests that the methodology used in his paper should "provide a useful point of departure for a second-stage analysis geared toward finding the determinants of productivity" (p. 268), i.e., an analysis not developed in his paper. This is exactly what we aim to do in the present analysis.

4. Estimating cross-country TFP levels in dynamic panel: small sample problems

The first problem to solve when we estimate a dynamic panel data model such as the one represented by equation (11) is which estimator suits our case better. To this aim we carefully compare the results obtained by using three different estimators: LSDV, Arellano and Bond (1991) and Kiviet (1995). In our choice of estimators, we do not include the system-GMM suggested by

[20] The Levin *et al*. (2002) panel unit-root test performed on the demeaned GDP series reject the hypotheses that series are nonstationary.
[21] The use of the 2004 observation, available for a group of countries, would have drastically reduced the available cross-country sample.
[22] See Jorgenson (2005).
[23] We use average years of schooling of the population over 15 years of age. See Barro and Lee (2000).

Blundell and Bond (1998) and Minimum Distance, both used by Islam (2003a). Reasons for this choice are as follows. First, the theoretical restrictions on which the system-GMM estimator is based do not hold in this context.[24] Second, the use of the Minimum Distance estimator has been highly criticised within the growth literature and, apart from Islam (2003a), there is a lack of empirical analysis that compares the performance of this estimator with other available estimator.[25]

Concerning the estimators we adopt, the LSDV one, while consistent for large T, is characterised by small sample problems and it is known to produce downward biased estimates in small samples.[26] Similar problems may be detected for the Arellano and Bond (1991) estimator (GMM-AB from now on). It has recently been shown that, when T is small, and either the autoregressive parameter is close to one (highly persistent series), or the variance of the individual effect is high relative to the variance of the transient shock, then even the GMM-AB estimator is biased and, in particular, downward biased.[27]

Our third estimator is based on Kiviet (1995), a paper that addresses the problem of the LSDV finite sample bias by proposing a small sample correction. Monte Carlo analysis (Kiviet, 1995; Judson and Owen, 1999) finds that for balanced panel and small (less or equal to ten) or moderate T (T=30), such as the one we usually find in convergence literature, LSDV estimates corrected for the bias (KIVIET from now on) have more attractive properties than other available estimators.[28] More recently, Everaert and Pozzi (2007) confirm this result and show that for samples similar to ours KIVIET consistently outperforms GMM-AB.[29]

Let us now turn to our specific case. Our panel includes the period 1960-2003 for 76 countries. Using the five-year time span (or $\tau = 5$) implies that we are left with T=10 observations for each country. Given the dimension of our panel and the above discussion, the KIVIET estimator should be preferred. However, since there is a yet unsolved debate on which technique is clearly superior in finite samples, in the following analysis we will use all the above-listed estimators and will compare their results in order to assess their robustness and plausibility.

Estimates of TFP levels over the whole sample period obtained by means of standard pooling OLS, LSDV, GMM-AB and KIVIET, are reported in Table 1. For each regression we

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[24] In particular, this methodology requires that first-difference Δy_{it} are not correlated with μ_i (see Bond *et al.*, 2001), and this implies that to implement this estimator we need to assume the absence of technological catching-up. If efficiency growth is related to initial efficiency, the first difference of log output might be correlated with the individual effect.

[25] See Caselli *et al.* (1996).

[26] For more on dynamic panel data see Baltagi (2003).

[27] See Blundell and Bond (1998) and Bond *et al.* (2001).

[28] In particular, these Monte Carlo studies explicitly analyse typical macro dynamic panels and find that for $T \leq 20$ and $N \leq 50$, the KIVIET and Anderson-Hsiao estimators consistently outperform GMM-AB. Moreover, despite having a higher average bias, KIVIET turns out to be more efficient than Anderson-Hsiao.

[29] We use the results obtained with the following sample: N=100, T=5 or T=10, lagged dependent variable coefficient equal to 0.8. Note that, differently from us, Everaert and Pozzi conclude in favor of a bias correction based on an iterative bootstrap procedure. Nevertheless, results based on of the analytical bias-corrected estimator (the one we use in our study) are very similar.

include both our estimates and the implied value of the structural parameter $\hat{\lambda}$, i.e. the speed of the convergence parameter.

In analysing our results, we follow the procedure proposed by Bond *et al.* (2001). Their suggestion is to use the results obtained with LSDV and OLS as benchmarks to detect a possible bias in our other estimates. Since in dynamic panels the OLS coefficient in the lagged dependent variable is known to be biased upwards and the LSDV one downwards, Bond *et al.* (2001) suggest that the true estimate should lie between the two. This procedure is consistent with the literature on partial identification where, as Manski (2007) puts it, "a parameter is partially identified if the sampling process and maintained assumptions reveal that the parameter lies in a set, its 'identification region', that is smaller than the logical range of the parameter but larger than a single point". In this specific case, since we presume that the true parameter values lie somewhere between $\hat{\beta}_{ols}$ and $\hat{\beta}_{LSDV}$, we expect its true value to be between 0.95 and 0.80 (as shown in Table 1) and we will exclude from our analysis estimators that produce results out of this range.

When equation (11) is estimated with LSDV (Model 2) we find, as said above, an AR(1) coefficient of 0.80 and a correspondingly relatively high speed of convergence of 4.4%. Among the regressors, both the coefficients on the lagged dependent variable and on population growth are significant and have the expected sign, while the coefficient on human capital is not significant. These results will be confirmed when other estimation procedures are used.

Table 1: Estimation of the augmented Solow model

Sample: 76 Countries, 1960-2003 (5 years time-span*)
Dependent variable: $\ln(y_{i,t})$
Observations: 608

	1 **OLS**	**2** **LSDV**	**3** **KIVIET**	**4** **GMM-AB1**	**5** **GMM-AB2**
$\ln(y_{i,t-5})$	0.950	0.803	0.927	0.836	0.833
	(0.009)	(0.022)	(0.045)	(0.035)	-0.054
$\ln(s)$	0.069	0.073	0.063	0.077	-0.001
	(0.010)	(0.014)	(0.018)	(0.022)	(-0.020)
$\ln(n+g+\delta)$	-0.273	-0.223	-0.250	-0.265	-0.369
	(0.043)	(0.066)	(0.074)	(0.099)	(0.080)
Human Capital	0.006	-0.013	-0.021	-0.028	-0.038
	(0.004)	(0.009)	(0.011)	(0.015)	(0.014)
lambda	0.010	0.044	0.015	0.036	0.037
Sargan test (p-value)				0.37	0.28
AB-2 test (p-value)				0.56	0.27

Notes:
Standard errors in parenthesis;
LSDV is the Least Squares with Dummy variables estimators;
KIVIET is the LSDV estimator with the Kiviet (1995) correction proposed by Bruno (2005);
Bootstrap standard errors in KIVIET (no. of repetitions = 500);
GMM-AB1 is the Arellano-Bond (1991) estimator under the assumption that x's are predetermined;
GMM-AB2 is the Arellano-Bond (1991) estimator under the assumption of x's strictly exogneous;
lambda is the corresponding (conditional) convergence coefficient.
**We include the 2003 observation as our last observation*

As expected, the use of the Kiviet correction procedure increases the LSDV parameter. In Model 3 (KIVIET), the coefficient of the lagged dependent variable is 0.93, with a decrease in the corresponding speed of convergence coefficient from 4% to 1.5%. Clearly KIVIET satisfies the above-quoted Bond *et al.* (2001) criterion as the estimated AR(1) coefficient lies between $\hat{\beta}_{ols}$ and $\hat{\beta}_{LSDV}$.[30]

Let us now extend our comparison to the other estimators. The GMM-AB estimator may be

[30] The analysis is performed through the XTLSDVC command in Stata with bias correction up to order O(1/T) and Anderson Hsiao as consistent estimator in the first step. Results are not sensitive to the use of alternative options: the Spearman rank order coefficient obtained comparing TFP obtained with KIVIET(Anderson-Hsiao) and KIVIET(Arellano-Bond) is extremely high, 0.997. Standard errors are calculated through bootstrapping.

performed under very different assumptions on the endogeneity of the included regressors. In this study we adopt two opposite hypotheses on the additional regressors $x's$. First, Model 4 (or Model GMM-AB1) in Table 1 assumes that all $x's$ are predetermined,[31] while Model 5 (or Model GMM-AB2) assumes instead that all regressors are strictly exogenous. Results in Table 1 on both the Sargan and the AB-2 test say that both specifications are valid and the estimated AR(1) coefficients do not suggest any presence of bias. Our choice is for Model 4 since the increase of the p-value of the Sargan test in GMM-AB1 indicates that treating the included regressors as predetermined makes it more difficult to reject the null.

With these estimates in hand we can compute our TFP measures. In our LSDV estimates the country dummy coefficients, $\hat{\mu}_i$, are almost invariably statistically significant. In particular, the F-test of the joint hypothesis that all the coefficients on our dummies are equal to zero is 3.41 (p-value=0.00) and clearly reject the hypothesis of no difference between countries.[32]

We obtain estimates of $\hat{A}(0)_i$ by means of eq. (8). In all cases, the TFP estimates $\hat{A}(0)_i$ are then used to compute $\tilde{A}(0)_i = \hat{A}(0)_i / \hat{A}(0)_{US}$, with $\hat{A}(0)_{US}$ being the estimated TFP value for the USA. Table A1 in the Appendix shows the ranking of each country's TFP estimated value relative to USA, based respectively on LSDV, KIVIET and GMM-AB1.[33] The Spearman rank order coefficient shows that the TFP rankings remain rather constant across the different estimators. In particular, the Spearman coefficient between LSDV-KIVIET is 0.95, between KIVIET and GMMAB1 is 0.97, and between LSDV and GMM-AB1 is 0.99.

A closer inspection of our estimates would further reveal that best and worst performers are almost identical across the four estimators, as shown by the data reported in Tables 2(a)-(b). These Tables confirm some well known stylized facts, with the industrialised countries at the top of the technology ladder and African countries at the bottom. With reference to the leader country, both LSDV and GMM-AB1 indicate the USA as the TFP leader, while in the KIVIET estimates the USA are in fourth place, behind Taiwan, Hong Kong and Korea. Finally, our estimates strongly confirm that cross-country TFP differences are very wide (the standard deviations of TFP and of per capita GDP are 0.254 and 0.292 respectively), and that they are strongly associated with the cross-country differences in per capita GDP.

[31] For more on this see Baltagi (2003).
[32] Note that individual effects are not directly estimated when GMM-AB1 and KIVIET are used.
[33] A ranking based on a GDP per capita in 1960 is also reported in the Table A1 as a benchmark.

Table 2a: Relative TFP levels - Best 20					
LSDV		**KIVIET**		**GMM-AB1**	
United States	1.00	*Taiwan*	1.62	*United States*	1.00
Hong Kong	0.84	*Hong Kong*	1.23	*Australia*	0.71
Canada	0.75	*Korea, Republic oj*	1.20	*Canada*	0.70
Australia	0.75	*United States*	1.00	*Hong Kong*	0.70
Norway	0.73	*Australia*	0.68	*Norway*	0.58
Singapore	0.67	*Canada*	0.64	*Israel*	0.56
Israel	0.65	*Singapore*	0.64	*New Zealand*	0.55
Taiwan	0.63	*Israel*	0.60	*Taiwan*	0.52
Barbados	0.61	*Ireland*	0.56	*Barbados*	0.48
Switzerland	0.60	*Norway*	0.47	*Switzerland*	0.46
Japan	0.59	*Barbados*	0.45	*Ireland*	0.45
Denmark	0.59	*New Zealand*	0.39	*Japan*	0.45
Ireland	0.58	*Japan*	0.38	*Denmark*	0.44
Iceland	0.58	*Malaysia*	0.38	*Singapore*	0.44
New Zealand	0.57	*Iceland*	0.28	*Sweden*	0.44
Sweden	0.56	*Belgium*	0.25	*Korea, Republic oj*	0.42
Austria	0.56	*Sweden*	0.25	*Iceland*	0.40
Netherlands	0.55	*United Kingdom*	0.25	*United Kingdom*	0.40
United Kingdom	0.55	*Mauritius*	0.25	*Belgium*	0.40
Belgium	0.54	*Denmark*	0.25	*Netherlands*	0.39

Table 2b: Relative TFP levels - Worst 20					
LSDV		**KIVIET**		**GMM-AB1**	
Zambia	0.020	*Niger*	0.002	*Niger*	0.008
Niger	0.022	*Zambia*	0.003	*Togo*	0.009
Togo	0.022	*Togo*	0.003	*Zambia*	0.009
Malawi	0.023	*Mali*	0.005	*Mali*	0.010
Mali	0.025	*Nepal*	0.005	*Malawi*	0.011
Nepal	0.029	*Kenya*	0.006	*Nepal*	0.011
Kenya	0.032	*Malawi*	0.007	*Kenya*	0.015
Lesotho	0.041	*Senegal*	0.007	*Mozambique*	0.018
Senegal	0.041	*Jamaica*	0.010	*Senegal*	0.018
Uganda	0.041	*Nicaragua*	0.012	*Lesotho*	0.021
Mozambique	0.042	*Zimbabwe*	0.012	*Uganda*	0.021
Honduras	0.060	*Mozambique*	0.012	*Honduras*	0.030
Ghana	0.066	*Honduras*	0.014	*Pakistan*	0.032
Pakistan	0.067	*Lesotho*	0.015	*Zimbabwe*	0.033
India	0.071	*Uganda*	0.016	*Jamaica*	0.037
Zimbabwe	0.071	*Bolivia*	0.020	*India*	0.038
Syria	0.073	*Iran*	0.023	*Ghana*	0.038
Bolivia	0.078	*Pakistan*	0.026	*Syria*	0.042
Jamaica	0.082	*Cameroon*	0.028	*Bolivia*	0.043
Cameroon	0.089	*Jordan*	0.028	*Cameroon*	0.044

In fact, the Spearman rank order coefficient between our TFP KIVIET estimates and the 1960-2003 average per capita GDP levels is equal to 0.97.[34] To sum up, the pattern and the magnitude of TFP heterogeneity as measured by our estimates suggest that a potential for technological catch-up does exist for the lagging countries. In the next section we will estimate TFP at two points of time to assess to what extent that potential has materialized as an actual source of convergence.

5. Detecting technological convergence: Empirical results

To detect how much TFP convergence is present in our sample, we estimate TFP-levels for the following two sub-samples: 1960-1980 and 1985-2003. Estimating TFP-levels for our two subperiods further exacerbates the problems associated with small sample bias. As reported above, in such conditions Monte Carlo results show that KIVIET should be preferred over the other estimators. Moreover, as we will see presently, the KIVIET AR(1) coefficient stays within the estimated upper (OLS) and lower (LSDV) bounds in both subperiods, while the same is not true for the GMM-AB1 estimator.[35] As a consequence, in the remaining part of the paper we will do not report the results based on GMM-AB1 and focus on those based on KIVIET. As before, we estimate equation (11) and save the two different series of $\hat{\mu}_i$. Results are shown in Table 3, which shows the KIVIET estimates of the AR (1) coefficient together with the OLS and LSDV estimates.

The convergence coefficient is significant in both subperiods, while the other regressors are non significant in most cases, with the exception of $\ln(n+\delta+g)$, significant and with the expected sign in the second subperiods. As before, $\hat{\mu}_i$ are almost invariably significant. The F test enables us to reject the hypothesis of no difference between countries for both subperiods.[36] Again, we apply equation (8) to our KIVIET estimates to obtain two series of $\hat{A}(0)_i$, and then compute the two indexes $\tilde{A}_{i,t-1} = \hat{A}_{i,t-1} / \hat{A}_{US,t-1}$ (for the initial period, 1960-80) and $\tilde{A}_{i,t} = \hat{A}_{i,t} / \hat{A}_{US,t}$ (for the subsequent period, 1985-2003).

Our estimated TFP values for the two subperiods, and the change of the ranking of each country, are shown in Table A2 in the Appendix. Before analysing the whole distribution over the two subperiods, it is worth noticing that in our estimates the USA have moved from the second place in 1960-1980 to the leading position in 1985-2003, and that few countries have obtained remarkable positive changes of rank – among them, Korea (+27 positions), Singapore (+25),

[34] Lower correlation coefficient values are obtained when TFP estimates are compared with initial levels (1960) of per capita GDP: 0.85 (GDP-GMM), 0.87 (GDP-LSDV) and 0.71 (GDP-KIVIET).
[35] In particular, the GMM-AB1 AR(1) coefficient the in the second sub-sample is lower than the downward biased LSDV one. Results are available upon request.
[36] The value of the F-test for the joint hypothesis that all the coefficients on our country dummies are equal to zero is 1.92 for the first subperiod (p-value 0.00), and 4.25 for the second subperiod (p-value 0.00).

Table 3: Estimation of the augmented Solow model (two subperiods)

Sample: 76 Countries, 5 years time-span*
Dependent Variable: $ln\ (y_{i,t})$
Obs. 304

	OLS 1960-80	LSDV 1960-80	KIVIET 1960-80	OLS 1985-2003	LSDV 1985-2003	KIVIET 1985-2003
$ln(y_{i,t-5})$	0.949	0.587	0.744	0.964	0.527	0.788
	(0.014)	(0.060)	(0.140)	(0.012)	(0.043)	(0.093)
$ln(s)$	0.074	0.056	0.057	0.038	-0.019	-0.022
	(0.117)	(0.027)	(0.065)	(0.014)	(0.025)	(0.030)
$ln(n+g+\delta)$	-0.125	-0.206	-0.149	-0.367	-0.157	-0.348
	(0.064)	(0.136)	(0.24)	(0.055)	(0.077)	(0.106)
Human Capital	0.010	0.011	0.003	0.004	0.005	0.0005
	(0.005)	(0.020)	(0.044)	(0.005)	(0.016)	(0.021)
lambda	0.010	0.107	0.059	0.007	0.128	0.048

Notes:
Standard errors in parenthesis;
LSDV is the Least Squares with Dummy variables estimators;
KIVIET is the LSDV estimator with the Kiviet (1995) correction proposed by Bruno (2005);
Bootstrap standard errors in KIVIET (no. of repetitions = 500);
lambda is the corresponding (conditional) convergence coefficient.
**We include the 2003 observation as our last observation*

Taiwan (+23), Hong Kong (+19) and Thailand (+18). Notice that these are also the countries who have achieved high growth in GDP per capita. This association between TFP and GDP per capita growth is confirmed when we extend the analysis to the whole sample: the observed changes in the rankings of TFP and of GDP per capita are highly correlated (0.96). While obtaining fast growth in TFP is not simple, it appears to be a key factor to achieve fast GDP per capita growth.[37]

With regard to other characteristics of whole cross-country TFP distribution, the main one for our purpose is the absence of an overall process of TFP convergence. Comparing the values of the standard deviation for the two series of initial and subsequent TFP, we observe that TFP dispersion is virtually constant across the two subperiods (0.255 and 0.254 respectively). This lack of overall TFP convergence is further confirmed by Figure 1, which illustrates the absence of significant changes in the distribution between the initial TFP levels (straight line) and subsequent TFP levels (dotted line).

[37] See Young (1994) for a different view on the role of technology in the fast growth of some Asian countries.

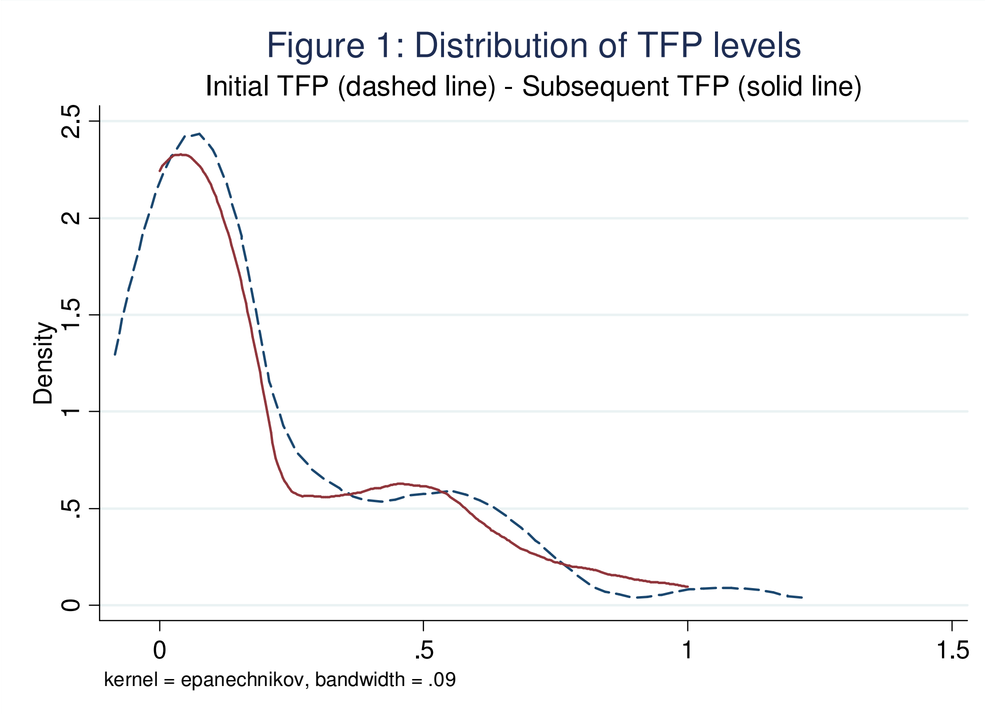
Figure 1: Distribution of TFP levels
Initial TFP (dashed line) - Subsequent TFP (solid line)
Density
0
.5
1
1.5
2
2.5
0
.5
1
1.5
kernel = epanechnikov, bandwidth = .09

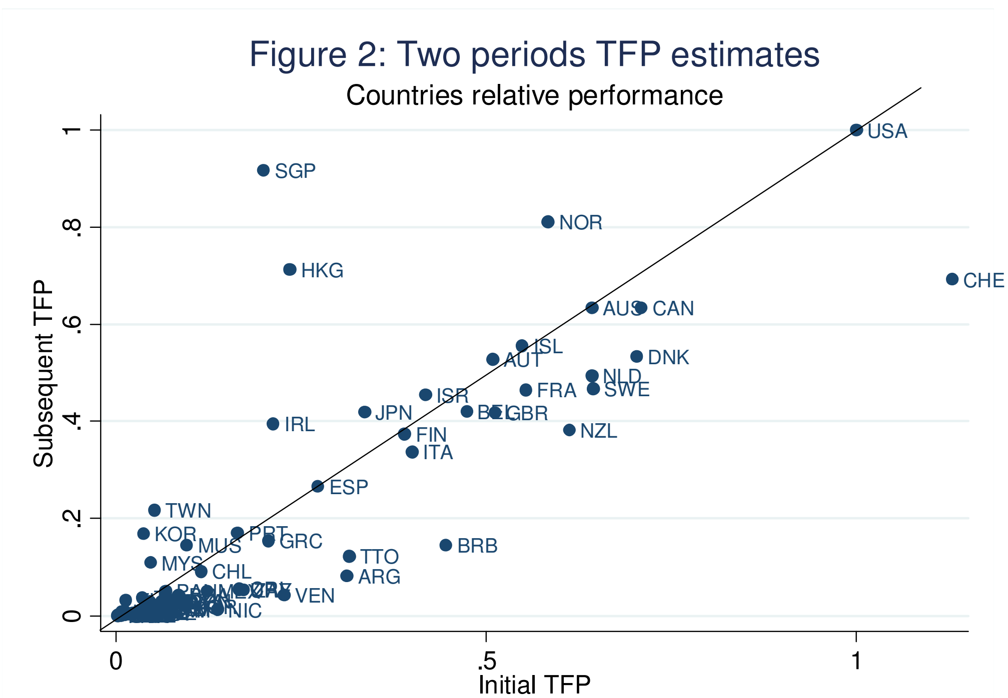
Figure 2: Two periods TFP estimates
Countries relative performance
Subsequent TFP
Initial TFP
0
.2
.4
.6
.8
1
0
.5
1
USA
SGP
NOR
HKG
CHE
AUS
CAN
ISL
AUT
DNK
NLD
SWE
FRA
ISR
GBR
JPN
IRL
FIN
NZL
ITA
ESP
TWN
KOR
MUS
PRT
GRC
BRB
TTO
MYS
CHL
ARG
VEN
NIC

In both periods, a twin-peak pattern does characterize the distribution, with less advanced countries, in particular, forming a well defined group. Similar results have been reported in previous studies.[38]

As it is well known, the absence of a strong process of TFP convergence may hide interesting but more complex dynamic patterns. Figure 2 shows the relationship between the two-period TFP estimates in our whole sample of countries. The 45 degree line shows the locus where each country's relative (to USA) TFP level would be time-invariant. Since most countries are below the 45 degree line, they have clearly underperformed with respect to the USA in terms of TFP growth. Only seven countries seems to be significantly improving on the USA's performance – namely, Korea, Taiwan, Singapore, Hong Kong, Thailand, Ireland and Malaysia. For few other countries, the initial gap decreases, but far less significantly.[39]

The robustness of these results has been assessed using a different specification of the model and a different estimator. In particular, almost identical results have been obtained replicating the whole KIVIET analysis excluding human capital from our regressions, and using non Kiviet-corrected LSDV estimates of $\tilde{A}(0)_i$.

6. Technology convergence and the role of human capital

In sections 4 and 5 above we noticed that human capital was never significant in our regression analysis on GDP per capita convergence. This is not the end of our search for a role of human capital in growth and convergence, however. The Nelson-Phelps approach[40] to technology diffusion suggests the existence of a different and less direct role played by human capital in growth. In particular, in Nelson and Phelps (1966) human capital stocks determine to what extent a lagging country can extract technological spillovers from an existing gap between its technology level and the world technology frontier (or the technology adopted in a leader country).

Our estimates of TFP levels enable us to test this hypothesis. Table 4 below shows the results of several OLS cross-section regressions[41] with our measure of TFP growth rates (1960-2003 averages[42]) as the dependent variable, and the initial value of TFP and the level of human capital among a number of different regressors. Due to data availability, in this section the sample is

[38] For instance, Feyrer (2003), using a sample ranging from 1970 to 1989, shows that the productivity residual seems to be moving towards a twin peaked distribution with the low peak in productivity emerging as particularly robust result.
[39] See also Figure A1 in the Appendix, where the relationship between on TFP growth and initial levels is shown.
[40] For more on this see Aghion and Howitt (1998) and Hojo (2003). This second study uses fixed effect to estimate TFP and finds a positive role of human capital in explaining cross-country differences in TFP levels.
[41] All results in both Table 4 and 5 report robust standard errors. Note that our conclusions are not sensitive to the standard error in use: results with the usual OLS standard errors are, in fact, very similar.
[42] As in Benhabib and Spiegel (2005), we calculate the average TFP growth rate as the log-difference between the estimated final and initial TFP divided by the relevant time span.

reduced from 76 to 73 countries.[43] In all the regressions the human capital index, H_i , is defined as the average value of our initial subperiod, 1960 to 1980[44]. All our regressions have been replicated using the 1960 human capital stocks to better control for possible endogeneity problems, but our results did not change significantly.[45] We favor the use of the average 1960-80 values because during the first subperiod many countries went through take rapid increases in education attainments.

We start with a conditional convergence model, with human capital as the main conditioning factor. Using our TFP estimates we can thus regress:

$$GRA_i = \psi_o + \psi_1 \tilde{A}(0)_i + \psi_2 H_i + \varepsilon_i \tag{13}$$

where GRA_i represents the annual average 1960-2003 growth rate of relative TFP $\tilde{A}_i = \hat{A}_i / \hat{A}_{US}$, $\tilde{A}(0)_i$ is the initial level of relative TFP and H_i is, as said above, the stock of human capital in the population. Differently from a standard GDP convergence analysis, equation (13) is broadly consistent with the Nelson and Phelps (1966) original idea that human capital stocks determine to what extent a lagging country can profit – through technological spillovers – from a given technology gap. Indeed, the Nelson-Phelps hypothesis postulates a process of conditional convergence in which the conditioning factor is H: as a consequence, in cross-country growth regressions $\tilde{A}(0)_i$ is expected to exhibit a significant inverse relation with GRA_i, and H_i a positive one.[46]

Model 1 in Table 4 confirms that initial human capital stocks are positively correlated with TFP growth rates, while Model 2 confirms the lack of absolute convergence in TFP levels (see also section 5 above). Model 3 implies that a process of convergence conditional to the average stock of human capital in the population does take place. As expected, the coefficient of the initial TFP value is negative and significant, and the coefficient of human capital is positive and significant.

To be more specific about the role played by human capital in this technology catch-up process, we use a model developed by Benhabib and Spiegel (2005). This model uses the original formulation of the catch-up term proposed by Nelson and Phelps (1966), characterized by the interaction between H and TFP. Besides, Benhabib and Spiegel (2005) extend significantly the Nelson-Phelps approach to include the possibility that, unless a critical value of human capital stock

[43] We are excluding Lesotho, Mozambique and Nepal. For these countries we could not find data for social infrastructure, additional variables used in this analysis.
[44] See footnote 22.
[45] These results are available upon request.
[46] The cross-section implication of the Nelson-Phelps hypothesis can be summed up as follows: consider a sample of countries who are away from their stationary positions, and who are characterized by different values of (constant) human capital stocks and of TFP (measured in terms of the leader's level). In such a sample all countries converge towards the common long-run growth rate, with their transitional TFP growth rate explained by their current technology gaps and human capital stock.

is reached, the catch-up mechanism is not activated. This extension is based on a "logistic" model of technology diffusion (see below). Thus, this model allows us to answer two related questions concerning the relationship between human capital and technology growth and adoption: first, how important is the Nelson-Phelps hypothesis in explaining the cross-country variance in TFP growth rates? Second: can a low level of human capital stock make it impossible for a lagging country to exploit its technology gap? In other words, can lagging countries be split in two different clubs (converging v non converging ones), according to their level of human capital?

As Benhabib and Spiegel (2005) show, the linear version of the logistic model can be written as:

$$\frac{\dot{A}_i}{A_i} = gH_i + cH_i\left(1 - \frac{A_i}{A_L}\right) = (g+c)H_i - cH_i\left(\frac{A_i}{A_L}\right), \tag{14}$$

where L identifies the "leader" country (the USA, in our panel). In this model, TFP growth depends on two factors: first, a country's own innovation capability, that in turn depends on its stock of human capital (gH_i); second, an interactive component, $cH_i(A_i/A_L)$, that should capture the process of catch-up described by the Nelson-Phelps hypothesis, in which the rate of technology diffusion depends on the existing technology gap and, again on the stock of human capital.

In this model, as A_i/A_L goes to zero $\dot{A}_i/A_i$ tends to a finite value, namely $(g+c)H_i$. An implication of this is that even an extremely large gap may not be sufficient to allow a lagging country to grow faster than the leading one, and therefore to be part of a "converging club". This setting extends the original hypothesis developed in Nelson and Phelps (1966) and in Benhabib and Spiegel (1994), in which all countries are supposed to be able to (conditionally) converge, whatever their level of human capital.[47]

Formally, since growth in the leading country is equal to gH_L, the condition for the lagging one to catch-up is:

$$H_i^* = \frac{g(H_L)}{g+c} \tag{15}$$

where H_L is the human capital stock of the leader nation. So, for catch up to take place, the stock of human capital in the lagging country has to be larger than a critical value defined by H_i^*. Whenever this condition is not met, divergence will occur because too small human capital stocks do not allow

[47] In those two models, a level of the technology gap always exists that allows a lagging country to converge towards a steady-state in which levels of TFP are different, depending on levels of H, but TFP growth rates are equalized across countries.

a country to exploit the potential advantage associated with its backwardness. To transfer technology from abroad, backwardness needs to be offset by enough human capital.

The main empirical implications of this model may be examined using a cross-country regression model on TFP growth defined by:

$$GRA_i = \lambda_0 + \lambda_1 H_i - \lambda_2 [H_i \cdot \tilde{A}(0)_i] + \varepsilon_i \tag{16}$$

where $\lambda_1 = (g + c)$ and $\lambda_2 = c$. In this case, point estimates with $\hat{\lambda}_2 > \hat{\lambda}_1$ indirectly imply a rejection of the model since a negative point estimate of g would represent an implausible result.

In Model 4 we regress equation (16) and find that, as expected, human capital is positive and significant while the interactive term is negative and significant. Moreover, we find that $\hat{\lambda}_1 > \hat{\lambda}_2$, thus implying a plausible positive point estimate of g.

As for the existence of a critical value of H as defined by equation (15) above, our estimates yield the following, and perhaps surprising,[48] result: the value of average (1960-80) years of schooling under which countries would diverge in TFP from the leader is 0.89. Within our panel of countries, this value is very low: only Mali and Niger are below this human capital threshold. All other countries are supposed to have enough human capital to be able to activate the Nelson-Phelps mechanism of technology adoption from abroad. In other words, our estimates of the logistic model give strong support to the original version of the Nelson-Phelps hypothesis, in which the technology distance from the leader represents an opportunity for all the lagging countries.

The robustness of our results has been further tested by introducing various measures of institutional quality. The importance of institutional quality (or "social infrastructure") in the explanation of the cross-country distribution of TFP levels has gained more and more attention in the last few years, starting from the seminal contribution by Hall and Jones (1999).[49] In their view, social infrastructure is formed of "…the institutions and government policies that determine the economic environment within which individuals accumulate skills, and firms accumulate capital and produce output" (p. 84). In particular, a good social infrastructure should limit the scope for rent-seeking and other unproductive activities and favor the adoption of new ideas and new technologies from abroad. Moreover, controlling for institutional quality is important since human capital can act as a proxy for it (Tabellini 2007, Guiso 2007).

Our first index of social infrastructure, "GADP", is a widely used cross-country index of property right protection (see Knack and Keefer, 1995; Hall and Jones, 1999; Tabellini, 2007).[50] As

[48] Benhabib and Spiegel (2005) find that 27 out of 75 countries were below their estimated threshold of H in 1960. Interestingly, the number of countries below the threshold decreases dramatically in time: using the 1995 values of H, only 4 countries were still below the estimated critical value.

[49] See also Acemoglu *et al.* (2001), Parente and Prescott (1999), Tabellini (2007).

[50] See the *International Risk Guide* compiled by Political Risk Services. GADP (namely, "government anti diversion policies") is formed by the average of five categories, namely: (i) corruption, (ii) risk of expropriation, (iii) government

in Hall and Jones (1999), we also use a second measure of social infrastructure, obtained by computing a simple average of GADP and an index of openness to trade, based on Sachs and Warner (1995).[51]

Table 4: TFP convergence, average years of education and social infrastructure

OLS, 73 Countries **Dependent variable: average TFP growth 1960-2003**								
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Human Capital	0.009 (0.002)		0.016 (0.004)	0.017 (0.004)	0.009 (0.003)	0.009 (0.003)	0.01 (0.004)	0.009 (0.003)
Initial TFP		0.055 (0.016)	-0.075 (0.033)		-0.155 (0.038)	-0.115 (0.029)		
*HK*TFP*				-0.010 (0.004)			-0.015 (0.004)	-0.010 (0.003)
GADP					0.210 (0.035)		0.174 (0.032)	
GADP&Openess						0.137 (0.019)		0.063 (0.014)
R^2	0.26	0.09	0.31	0.33	0.54	0.55	0.51	0.47

Notes:

Robust standard errors in parenthesis;

Human capital is the total average years of schooling in the total population aged 15 and over. See Barro and Lee (2000). Data are averages of the period 1960-80;

*The variable HK*TFP is formed by multiplying Initial TFP times Human Capital;*

The variable GADP is formed by the average of five categories, namely: (i) corruption, (ii) risk of expropriation, (iii) government repudiation, (iv) law and order, (v) bureaucratic quality. See also footnote 48.

Overall, our results show that the two measures of institutional quality are always positive determinants of the TFP convergence process. In Models 5 and 6 we have TFP growth rates as the dependent variable and the initial value of TFP, human capital and two proxies of social infrastructure among regressors. The coefficient on average years of schooling does decrease from 0.016 to 0.009 but remains positive and significant in both regressions, while coefficients on both proxies for social infrastructure are rather stable. Similar results are obtained using the logistic specification (Models 7 and 8). In particular, these models confirm the significant role of the catch-

repudiation, as measures of the government as a potential diverter for private investment; (iv) law and order, (v) bureaucratic quality as measures of the capability of the government as a protector for private investment. See Hall and Jones (1999) and Knack and Keefer (1995) for further details.

[51] As Hausmann and Pritchett (2005) remind us, the Sachs-Warner dummy is a measure that captures broad economic reforms more than just an index about trade openness. We have also performed the same analysis using only the index of openness to trade obtaining almost identical results.

up term, while they shed some doubt on the role of H as a determinant of own-country innovation.

In sum, the broad set of results shown in this section yields strong evidence in favor of the hypothesis that human capita is an important positive determinant of the process of technology catch-up for the great majority of countries in our sample. Indeed, the Nelson-Phelps hypothesis turns out to valid for nearly all countries in our panel, to be robust to different model specification and to the inclusion of various indexes of social infrastructure.

It also shows that the influence exerted by human capital on TFP growth is independent – to a significant extent – of a country's institutional quality. This result is in contrast with the idea that "the determinants of social infrastructure affect [productivity] only through social infrastructure and not directly", as put forward by Hall and Jones (1999), p. 99. It is also in contrast with previous results where the role of human capital in TFP growth turned out to be very weak in the presence of controls for trade policy (Miller and Upadhyay, 2000) and other social infrastructure controls (Benhabib and Spiegel, 2005).

The confirmation of a direct role played by human capital is worth underlying because of the obvious but important policy implications about the effectiveness of investment in education, even in countries where social infrastructure is lacking. This conclusion would be even stronger if education play a second, less direct role in TFP growth through the influence exerted on social infrastructure. As Glaeser (2001) suggests, "schools are a primary area where social capital is developed", and perhaps where favorable conditions for the creation of institutions of good quality are laid down.

7. Stages of developments and different educational attainments

Finally, we run our cross-country regressions on GRA_i using again equation (13) but decomposing total schooling into three components: average years of primary, secondary and tertiary schooling.[52] Recent catch-up models suggest that imitation and innovation may require different types of skills (Vandenbussche *et al.*, 2006). In particular, innovation activities are certainly influenced by higher levels of education, while imitation may be performed by labour forces with lower levels of skills. We may thus expect a different role on TFP growth for different levels of education.

[52] They are the average years of primary, secondary and tertiary education in the total population aged 15 and over. See Barro and Lee (2000). Data are averages of the period 1960-80. Redoing regressions in Tables 4 and 5 using initial year (1960) human capital observations to better control endogeneity problems changes the results only trivially.

Table 5: TFP convergence, different levels of education and social infrastructure

Cross section OLS, 73 Countries
Dependent variable: average TFP growth 1960-2003

	1	**2**	**3**	**4 High-tech**	**5 Low-tech**
Initial TFP		-0.077	-0.117	-0.049	-0.272
		(0.035)	(0.037)	(0.016)	(0.073)
GADP			0.212	0.158	0.235
			(0.036)	(0.035)	(0.047)
Degree	-0.105	-0.077	0.004	0.074	-0.10
	(-0.055)	(0.057)	(0.048)	(0.034)	(0.092)
Secondary School	0.019	0.030	0.021	-0.005	0.045
	(0.009)	(0.012)	(0.009)	(0.005)	(0.013)
Primary School	0.012	0.015	0.005	-0.008	0.007
	(0.004)	(0.005)	(0.005)	(0.004)	(0.008)
R^2	0.30	0.34	0.56	0.67	0.64

Notes:
Robust standard errors in parenthesis;
The variable GADP is calculated using data on (i) corruption, (ii) risk of expropriation, (iii) government repudiation, (iv) law and order, (v) bureaucratic quality. See footnote 48;
Degree, secondary school and primary school are the average years of primary, secondary and tertiary education in the total population aged 15 and over. See Barro and Lee (2000). Data are averages of the period 1960-80;
The High-tech group is formed by 21 countries whose initial TFP level is greater than 0.3, while Low-tech are the remaining 52 countries. See also footnote 51.

Table 5 shows how equation (13)[53] performs when we decompose human capital in all three levels of education. We find that only the lower levels of schooling seems to matter in the simpler specifications (Models 1 and 2), while only secondary schooling stays positive and significant once our social infrastructure indicator are used as controls (Model 3). However, we also find that these results change significantly if we divide the sample between initial high-tech and low-tech countries. In Model 4 we use the specification of Model 3 for a sample to 21 High-tech countries,[54] whose an initial level of relative TFP larger than 0.3; in Model 5 we do the same for a sample formed by the 52 remaining low-tech countries. As for the choice of the cut-off value, the latter is based on Figure 1, which indirectly suggests the existence of two clubs, with a cut-off value of the initial TFP level placed approximately between 0.3-0.4.

Our estimates of Models 4 and 5 show that for advanced countries only tertiary education

[53] We exclude from this analysis the logistic specification since it has previously produced implausible results.
[54] These are defined by countries with and initial relative level of TFP larger than 0.3, and include Argentina, Australia, Austria, Barbados, Belgium, Canada, Denmark, Finland, France, Iceland, Israel, Italy, Japan, Netherland, New Zealand, Norway, Sweden, Switzerland, Trinidad & Tobago, UK and USA.

seems to matter while for Low-tech countries only the secondary school coefficient shows a significant and positive sign. These results would be even stronger if we used as cut-off value of 0.4 instead of 0.3, implying a smaller group of High-tech economies.[55] To sum up, these results are suggestive rather than conclusive. Nevertheless, they do suggest that the principal gains from education for laggard countries, in terms of TFP growth at least, stem from investing in lower levels of education. Conversely, in more advanced countries investing in tertiary education seems to pay higher returns, presumably because growth relies more on own-innovation, an activity that requires a higher skilled labour force than imitation.

8. Conclusion

The aim of this paper was to assess the existence of technology convergence across a sample of 76 countries between 1960 and 2003. Different methodologies have been proposed to measure TFP heterogeneity across countries, but only a few of them try to capture the presence of technology convergence as a separate component from the standard (capital-deepening) source of convergence. To distinguish between these two components of convergence, we have proposed and applied a fixed-effect panel methodology. Robustness of results is assessed using different estimation procedures such as simple LSDV, Kiviet-corrected LSDV, and GMM *à la* Arellano and Bond (1991).

Our empirical analysis confirms the presence of a high and persistent level of TFP heterogeneity across countries. Furthermore, we do not find evidence of a global process of TFP convergence, since the dispersion of the estimated TFP levels remained constant through time. Within this aggregate persistence, important changes are detected by our analysis. In particular, differently from previous results reported in the literature, based on shorter sample periods, we find that the USA, the TFP leader, is currently distancing itself further from the rest of the countries. In this new context, European countries, with few exceptions, seem to worsen their relative TFP ranking, while East Asian countries appear as the major winners.

As for why cross-country TFP gaps tend to be persistent, we find that cross-country TFP growth follows a process of convergence conditional to the stock of human capital in the population. Following Benhabib and Spiegel (2005), we also test whether a critical value of human capital stock has to be reached in a lagging country in order to activate the mechanism of technology catch-up. In contrast with previously reported evidence, we find little evidence in favor of this hypothesis, since in our results even very low level of human capital stocks allow a country to enter a "conditional TFP convergence club". Taken together, these results strongly support the original version of the Nelson and Phelps (1966) hypothesis, in which the technology distance from the leader

[55] In this case the High-tech sample reduces to 17 countries (Argentina, Finland, Japan and Trinidad & Tobago excluded).

represents a source of conditional convergence for all (or at least for the great majority of) the lagging countries. Moreover, results also imply there is a plausible link between stages of development and returns to different levels of education as suggested by recent studies.

Our results on the important role played by human capital in the catch-up mechanism are robust to the inclusion of various and widely used indexes of social infrastructure and openness. To put it in a nutshell, investing in human capital still represents one of the best options available to developing countries beset by too low per capita incomes.

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Table A1: Rank of relative TFP levels obtained using different estimators

Countries	Rank with GDP	Rank with LSDV	Rank with KIVIET	Rank with GMM-AB1
Algeria	38	46	55	51
Argentina	20	32	39	31
Australia	6	4	5	2
Austria	12	17	22	21
Barbados	15	9	11	9
Belgium	13	20	16	19
Bolivia	55	59	61	58
Brazil	41	39	47	43
Cameroon	57	57	58	57
Canada	8	3	6	3
Chile	31	33	30	32
Colombia	44	41	42	40
Costa Rica	34	31	27	30
Denmark	3	12	20	13
Dominican Republic	50	38	34	38
Ecuador	52	50	49	47
El Salvador	43	47	53	50
Finland	14	23	26	23
France	9	21	24	22
Ghana	71	64	44	60
Greece	23	27	29	28
Guatemala	45	48	51	53
Honduras	58	65	64	65
Hong Kong	26	2	2	4
Iceland	19	14	15	17
India	65	62	52	61
Indonesia	62	52	41	54
Iran	33	49	60	55
Ireland	25	13	9	11
Israel	17	7	8	6
Italy	16	24	32	24
Jamaica	37	58	68	62
Japan	18	11	13	12
Jordan	39	53	57	52

Table A1 (continue)

Countries	Rank with GDP	Rank with LSDV	Rank with KIVIET	Rank with GMM-AB1
Kenya	67	70	71	70
Korea, Republic of	53	22	3	16
Lesotho	74	69	63	67
Malawi	76	73	70	72
Malaysia	54	28	14	27
Mali	75	72	73	73
Mauritius	40	26	19	25
Mexico	35	37	40	37
Mozambique	72	66	65	69
Nepal	73	71	72	71
Netherlands	5	18	21	20
New Zealand	7	15	12	7
Nicaragua	32	56	67	56
Niger	68	75	76	76
Norway	10	5	10	5
Pakistan	64	63	59	64
Panama	42	35	25	33
Paraguay	47	42	38	39
Peru	36	51	56	49
Philippines	56	54	46	46
Portugal	27	30	36	34
Senegal	60	68	69	68
Singapore	28	6	7	14
South Africa	29	34	35	35
Spain	21	25	28	26
Sri Lanka	63	55	37	48
Sweden	4	16	17	15
Switzerland	1	10	23	10
Syria	69	60	50	59
Taiwan	49	8	1	8
Thailand	59	44	31	41
Togo	61	74	74	75
Trinidad &Tobago	22	29	33	29
Tunisia	51	43	43	44
Turkey	46	45	48	45
Uganda	70	67	62	66
United Kingdom	11	19	18	18
United States	2	1	4	1
Uruguay	30	36	45	36
Venezuela	24	40	54	42
Zambia	66	76	75	74
Zimbabwe	48	61	66	63

Table A2: Estimated TFP levels 1960-1980 and 1985-2003 KIVIET

Countries	Relative TFP levels 1960-80	ranking 1960-80	Relative TFP levels 1985-2003	ranking 1985-2003	*Change of rank*
Algeria	0.078	39	0.031	43	-4
Argentina	0.312	21	0.081	32	-11
Australia	0.643	6	0.634	7	-1
Austria	0.509	13	0.528	10	3
Barbados	0.446	15	0.144	28	-13
Belgium	0.474	14	0.420	15	-1
Bolivia	0.031	55	0.006	58	-3
Brazil	0.084	38	0.042	38	0
Cameroon	0.023	57	0.005	60	-3
Canada	0.710	3	0.634	6	-3
Chile	0.115	34	0.092	31	3
Colombia	0.062	43	0.029	44	-1
Costa Rica	0.166	29	0.056	33	-4
Denmark	0.704	4	0.534	9	-5
Dominican Republic	0.046	49	0.028	45	4
Ecuador	0.046	50	0.018	49	1
El Salvador	0.063	42	0.015	50	-8
Finland	0.390	18	0.374	20	-2
France	0.554	10	0.465	13	-3
Ghana	0.002	75	0.001	68	7
Greece	0.206	26	0.154	26	0
Guatemala	0.054	45	0.012	53	-8
Honduras	0.018	58	0.004	62	-4
Hong Kong	0.235	23	0.713	4	19
Iceland	0.549	11	0.556	8	3
India	0.006	69	0.004	63	6
Indonesia	0.011	61	0.010	55	6
Iran	0.095	36	0.031	42	-6
Ireland	0.213	25	0.395	18	7
Israel	0.418	16	0.455	14	2
Italy	0.400	17	0.338	21	-4
Jamaica	0.047	47	0.012	52	-5

Table A2 (continued)

Countries	Relative TFP levels 1960-80	ranking 1960-80	Relative TFP levels 1985-2003	ranking 1985-2003	*Change of rank*
Japan	0.336	19	0.419	16	3
Jordan	0.095	37	0.018	48	-11
Kenya	0.007	68	0.001	69	-1
Korea, Republic of	0.037	52	0.168	25	27
Lesotho	0.004	71	0.002	65	6
Malawi	0.002	76	0.000	76	0
Malaysia	0.047	48	0.109	30	18
Mali	0.003	74	0.001	71	3
Mauritius	0.096	35	0.145	27	8
Mexico	0.123	33	0.051	36	-3
Mozambique	0.007	66	0.001	70	-4
Nepal	0.004	73	0.001	67	6
Netherlands	0.643	7	0.494	11	-4
New Zealand	0.613	8	0.382	19	-11
Nicaragua	0.137	32	0.012	54	-22
Niger	0.008	63	0.001	74	-11
Norway	0.584	9	0.811	3	6
Pakistan	0.007	65	0.005	61	4
Panama	0.067	41	0.050	37	4
Paraguay	0.061	44	0.024	46	-2
Peru	0.070	40	0.015	51	-11
Philippines	0.031	56	0.010	56	0
Portugal	0.164	31	0.171	24	7
Senegal	0.012	60	0.002	66	-6
Singapore	0.200	27	0.917	2	25
South Africa	0.172	28	0.053	35	-7
Spain	0.273	22	0.266	22	0
Sri Lanka	0.008	64	0.009	57	7
Sweden	0.645	5	0.467	12	-7
Switzerland	1.130	1	0.692	5	-4
Syria	0.010	62	0.003	64	-2
Taiwan	0.052	46	0.217	23	23
Thailand	0.014	59	0.032	41	18
Togo	0.007	67	0.001	75	-8
Trinidad &Tobago	0.315	20	0.122	29	-9
Tunisia	0.036	53	0.037	40	13
Turkey	0.040	51	0.023	47	4
Uganda	0.005	70	0.001	72	-2
United Kingdom	0.512	12	0.418	17	-5
United States	1.000	2	1.000	1	1
Uruguay	0.166	30	0.053	34	-4
Venezuela	0.227	24	0.042	39	-15
Zambia	0.004	72	0.001	73	-1
Zimbabwe	0.034	54	0.006	59	-5

Figure A1: TFP growth versus initial levels