the review of income and wealth

Review of Income and Wealth
Series 57, Number 1, March 2011

INTERNATIONAL TFP DYNAMICS AND HUMAN CAPITAL STOCKS: A PANEL DATA ANALYSIS, 1960–2003

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This paper adopts fixed-effect panel methodologies to obtain TFP values for a sample of 76 countries from 1960 through 2003. Our results are robust to the use of different estimators (LSDV, Kiviet-corrected LSDV, and GMM). They show that TFP dynamics are characterized by a process of conditional convergence where most countries do not catch up with the U.S., and where human capital plays an important role in technology adoption, as suggested by Nelson and Phelps in 1966. Such a role is robust to the inclusion of controls for the quality of institutions in a country. Further, our results imply a plausible link between stages of development and returns to different levels of education. Finally, we calculate the minimum human capital level necessary to generate catch-up and find that virtually all countries are above that level—a result that again emphasizes the importance of human capital in technology diffusion.

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, world income distribution does not become less dispersed over time, with poor countries on average failing to grow faster than the rich ones (Pritchett, 2001; Durlauf *et al.*, 2005; Grier and Grier, 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, large differences in 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 that for many lagging countries this lever may not be as simple to use as a number of models would postulate.[2] Using data

Note: We thank participants to seminars held at the European Economic Association Annual Congress, Budapest, University of Barcelona, Luiss University (Roma) and Collegio Carlo Alberto (Torino). Financial support from the European Community under the FP7 SSH Project "Intangible Assets and Regional Economic Growth" grant n. 216813 is gratefully acknowledged.

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[1]On the role of TFP heterogeneity in cross-country analysis, see also Parente and Prescott (1999), Easterly and Levine (2001), and Lucas (2000) among many others. Few economists dispute these findings. Among them see Young (1994) and, more recently, Baier *et al.* (2006).

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

on the diffusion of 23 technologies over more than two centuries, Comin and Hobijn (2004) observe that diffusion is far from instantaneous and that large differences exist in the rate of technology adoption even across the leading countries of the world economy.[3]

These large differences might be due to their human capital stocks being too low, as firstly suggested by Nelson and Phelps (1966), or to the insufficient quality or appropriateness of their institutions (Hall and Jones, 1999; Acemoglu *et al.*, 2001, 2006; Comin and Hobijn, 2009), 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 favoring cross-country diffusion of technology?

These are long-standing important questions. As maintained more than ten years ago by Bernard and Jones (1996), such questions call for direct analysis of the evolution of cross-country TFP levels over time. 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. Besides, empirical results are far from uniform. The available evidence ranges from supporting strong conditional convergence in TFP levels (e.g., Aiyar and Feyrer, 2002; Dowrick and Rogers, 2002; Benhabib and Spiegel, 2005, who all emphasize the positive role played by human capital),[4] to suggesting that the observed cross-country TFP dynamics are mostly due to random shocks. Other papers are more doubtful about the strength of technological diffusion as a systematic source of income convergence (among them, Kumar and Russell, 2002; Islam, 2003).

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 (2003), 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.[5] The main feature of this framework is that TFP levels are estimated by means of growth regressions in which the contribution of

[3]Comin and Hobijn (2004) study 20 technologies across 23 leading countries. The high variance in the rates of adoption is confirmed by Comin *et al.* (2008), who study the diffusion of 10 technologies across 185 countries.

[4]TFP growth is also the main contributor to GDP per capita convergence in Wong (2007), although in this paper the contribution of human capital is found to be negligible.

[5]See Di Liberto *et al.* (2008) for more details. 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 requires the use of large datasets. These problems may be present, for instance, with techniques such as growth/level accounting and DEA.

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.

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 estimator (Arellano and Bond, 1991). 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. It is worth underlining that this time span includes the 1990s,[6] 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 U.S. and the more developed economies as the major beneficiaries.[7] Our data are mainly from the *Penn World Tables* (2006), with the exception of human capital data, which are from Barro and Lee (2000),[8] and the indexes of institutional quality, which are based on data from the *International Risk Guide* and on openness to trade from Sachs and Warner (1995).

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 characterizes 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 countries' performances, differently from previous studies, our analysis shows that in recent years the U.S. has consolidated its long-standing leadership in cross-country TFP levels.

In relation to why cross-country TFP gaps tend to be persistent, we produce new evidence supporting one of the most influential hypotheses on technology convergence, developed by 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; and (iii) shows that even very low levels of human capital stocks allow a country to enter a "conditional TFP convergence club." Points (ii) and (iii) in particular differ from previous results reported in the literature. Point (ii) is in contrast with the idea that human capital is an outcome of a country's social infrastructure, and should not be regarded as an independent determinant of productivity (Hall and Jones, 1999), while point

[6]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.

[7]See Jorgenson (2005) and Inklaar *et al.* (2005).

[8]The sample of 76 countries is the largest obtainable with these datasets: Heston *et al.* (2006), version 6.2; and Barro and Lee (2000), human capital updated files.

(iii) challenges the idea that convergence is triggered only if a threshold level of human capital is reached (Tamura 1996; 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, even with a large sample of both developed and least developed countries, it is possible to identify a plausible link between stages of development and returns to different levels of education, as also suggested by recent studies (Aghion *et al.*, 2006; Vandenbussche *et al.*, 2006) that focus on OECD and "within country" samples.

The rest of the paper is organized as follows. In Section 2 we describe our chosen methodology to estimate TFP levels at different point in time, while in Section 3 we discuss how to select the estimator that suits our case better and present our evidence on degrees of cross-country TFP heterogeneity. Section 4 shows how much TFP convergence can be detected in our dataset, and Section 5 tests whether our estimated TFP growth rates are positively correlated with the observed human capital endowments. Finally, Section 6 shows some evidence on the specific role different levels of education play on TFP growth. Section 7 concludes.

2. A Panel Data Approach to Estimate TFP Convergence

Our aim is to investigate cross-country TFP heterogeneity and convergence using an appropriate fixed-effect panel estimator. Islam (1995) was among the first to suggest this econometric solution to the problem of controlling for TFP heterogeneity in convergence analysis.[9] 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:

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

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

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

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

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

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

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

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

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

where $A(0)_i$ represents the initial level of technology; s, n, and δ are, respectively, the saving rate, the population growth rate, and the depreciation rate; g is the exogenous rate of technological change,[10] assumed to be invariant across individual economies; α is the usual capital share of a standard Cobb–Douglas production function; and 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 (equation 7) that captures the growth rate of the technology frontier assumed constant across individuals. Once we have the estimated individual intercepts, we can obtain an index of TFP by computing:

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

Since TFP estimates include all unobservable components assumed to be different across countries but constant over time, such as technology gaps (more on this later), 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:

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

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

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

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

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[11]—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.[12] To this aim we further develop an approach first suggested by Islam (2003). However, in our choice of estimators, we do not include the system-GMM suggested by Blundell and Bond (1998) and Minimum Distance, both used by Islam (2003). 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.[13] Second, the use of the Minimum Distance estimator has been highly criticized within the growth literature and there is a lack of empirical analysis that compares the performance of this estimator with other available estimators.[14] In other words, the use of the Minimum Distance and system GMM to estimate fixed effects, and thus TFP levels do not represent an optimal choice in this context. Further, we use our TFP estimates to perform an analysis of the determinants of productivity not developed in his paper.

Our period of analysis is significantly longer than in most studies on cross-country TFP dynamics (i.e., 1960–90), and includes years strongly influenced by the introduction of IT technologies. In terms of TFP convergence, these latter years are important in that developments in IT have seen " . . . a rapidly rising source of aggregate productivity growth throughout the 1990s."[15] More precisely, we use PWT 6.2 data on GDP per worker 1960–2003 to estimate the following equation:

[11]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. See Section 5 for further details.

[12]Splitting a longer period into several sub-periods 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.

[13]In particular, this methodology requires that first-difference Δy_{it} are not correlated with μ_i (see Bond *et al.*, 2001); 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. See also Hauk and Wacziarg (2004).

[14]For more on the use of the MD estimator in growth analysis, see Caselli *et al.* (1996) and Islam (2003).

[15]See Jorgenson (2005).

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

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

where $\bar{y}_t$ and $\bar{x}_t$ 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.[16] 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, despite using a five-year time span, we also include the 2003 observation as our last observation in order to embrace the longest possible sample.[17] The additional regressor $x_{3,it}$ is an index of a country's stock of human capital based on the average years of schooling.[18] 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.

3. Estimating Cross-Country TFP Levels in a 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. The answer is not simple since, as we shall see, even consistent estimators are characterized by small sample problems. To this end we carefully compare the results obtained by using three different fixed effects estimators: LSDV, Arellano and Bond (1991), and Kiviet (1995).

As mentioned above, 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. Estimates over the whole sample period are reported in Table 1. For each regression we include both our estimates and the implied value of the structural parameter $\hat{\lambda}$, i.e. the speed of the convergence parameter.

In analyzing our results, we follow the procedure proposed by Bond *et al.* (2001) which is consistent with the literature on partial identification.[19] Their suggestion is to use the results obtained with LSDV and a pooling OLS estimator as benchmarks to detect a possible bias in our other estimates. In particular, results show that in dynamic panels the OLS coefficient in the lagged dependent variable

[16]The Levin *et al.* (2002) panel unit-root test performed on the demeaned GDP series rejects the hypotheses that series are non-stationary.

[17]Therefore, our sample includes the following years: 1960, 1965, 1970, 1975, 1980, 1985, 1990, 1995, 2000, and 2003. The use of the 2004 observation, available for a group of countries, would have drastically reduced the available cross-country sample.

[18]We use average years of schooling of the population over 15 years of age. See Barro and Lee (2000).

[19]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."

TABLE 1
Estimation of the Augmented Solow Model

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

	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
Obs	608	608	608	608	608
Sargan test (p-value)				0.37	0.28
AB-2 test (p-value)				0.56	0.27

Notes:
Standard errors in parentheses.
LSDV is the least squares with dummy variables estimator.
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 exogenous.
lambda is the corresponding (conditional) convergence coefficient.
*We include the 2003 observation as our last observation.

is known to be biased upwards. Conversely, LSDV, while consistent for large T, is characterized by small sample problems and it is known to produce downward biased estimates on the AR(1) coefficient in small samples. Therefore, in our specific case, since we presume that the true parameter value lies somewhere between $\hat{\beta}_{ols}$ and $\hat{\beta}_{LSDV}$, we expect it 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 indicated above, an AR(1) coefficient of 0.80 and a correspondingly relatively high speed of convergence of 4.4 percent. 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.[20] These results will be confirmed when other estimation procedures are used.

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. 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

[20]The lack of empirical support for human capital in convergence regressions based on large international datasets is a well known problem. A number of possible explanations have been put forward. See Pritchett (1997), Temple (1999), and Krueger and Lindahl (2001).

4 to 1.5 percent. Clearly KIVIET satisfies the above-quoted Bond *et al.* (2001) criterion as the estimated AR(1) coefficient lies between $\hat{\beta}_{ols}$ and $\hat{\beta}_{LSDV}$.[21]

Let us now extend our comparison to the GMM–AB estimator.[22] This may be 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, while Model 5 (or Model GMM–AB2) assumes instead that all regressors are strictly exogenous.[23] Results in Table 1 on both the Sargan and the AB2 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 finally 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 = 0.00) and clearly rejects the hypothesis of no difference between countries.[24]

We obtain estimates of $\hat{A}(0)_i$ by means of equation (8). In all cases, the TFP estimates $\hat{A}(0)_i$ are then used to compute $\tilde{TFP}_i = \hat{A}(0)_i / \hat{A}(0)_{US}$, with $\hat{A}(0)_{US}$ being the estimated TFP value for the U.S. Table A1 in the Appendix shows the ranking of each country's TFP estimated value relative to the U.S., based respectively on LSDV, KIVIET, and GMM–AB1.[25] The Spearman rank order coefficient shows that the TFP rankings remain rather constant across the different estimators. In particular, the Spearman coefficient between LSDV and 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 the best and worst performers are almost identical across the four estimators, as shown by the data reported in Tables 2(a) and 2(b). These tables confirm some well known stylized facts, with the industrialized 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 U.S. as the TFP leader, while in the KIVIET estimates the U.S. is in fourth

[21]The analysis is performed assuming a 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.

[22]Note that Blundell and Bond (1998) and Bond *et al.* (2001) show 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 downward biased.

[23]In Models 4 and 5 we are not constraining the number of lags of the lagged dependent or endogenous variables for use as instruments. Thus, in Model 5 the set of instruments can be described by $z'_{it} = [y_{i,t-2\tau}, y_{i,t-3\tau}, \ldots, y_{i,1}, \Delta x'_{it}]$ with 35 over-identifying restrictions, while in Model 4 all regressors are assumed endogenous and thus their lagged levels (lagged from $t - 2\tau$ to 1) serve as instruments. In Model 4 the number of instruments increases significantly and this can weaken the estimation results. See Roodman (2009).

[24]Note that individual effects are not directly estimated when GMM–AB1 and KIVIET are used.

[25]A ranking based on a GDP per capita in 1960 is also reported in 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 of	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 of	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

place, behind Taiwan, Hong Kong, and South Korea. Finally, our estimates strongly confirm that cross-country TFP differences are 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 as the Spearman rank order coefficient between our TFP KIVIET estimates and the 1960–2003 average per capita GDP levels is equal to 0.97.[26]

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.

4. 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: 1960–80 and 1985–2003. Estimating TFP levels for our two sub-periods, both with $T = 5$, further exacerbates the problems associated with small sample bias. In such conditions Monte Carlo results show that KIVIET should be preferred over the other estimators.[27] Results find that for balanced panel and small ($T \leq 10$) 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]

Moreover, as we will see later, the KIVIET AR(1) coefficient stays within the estimated upper (OLS) and lower (LSDV) bounds in both sub-periods, while the same is not true for the GMM–AB1 estimator.[29] As a consequence, in the remaining part of the paper we do not report the results based on GMM–AB1 but 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 sub-periods, 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 sub-periods. 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 sub-periods.[30] Again, we apply equation (8) to our KIVIET estimates to obtain two series of $\hat{A}(0)_i$, and then compute the two indexes $T\tilde{F}P_{i,1} = \hat{A}_{i,1} \big/ \hat{A}_{US,1}$ (for the initial period, 1960–80) and $T\tilde{F}P_{i,2} = \hat{A}_{i,2} \big/ \hat{A}_{US,2}$ (for the subsequent period, 1985–2003). Our estimated TFP values for the two sub-periods, and the change of the ranking of each country, are shown in Table A2 in the Appendix.

[26]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).

[27]See Kiviet (1995), Judson and Owen (1999), and Everaert and Pozzi (2007). An exception can be found in Hauk and Wacziarg (2004) that suggest the use of a between estimator when measurement error is present. However, surprisingly, in their Monte Carlo analysis they do not consider the Kiviet estimator that is the preferred one in all other studies.

[28]In particular, these studies 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]In particular, in the second sub-sample the GMM–AB1 coefficient is lower than the downward biased LSDV one. Results are available upon request.

[30]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 sub-period (p = 0.00), and 4.25 for the second sub-period (p = 0.00).

TABLE 3

Estimation of the Augmented Solow Model (two subperiods)

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

	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
Obs	304	304	304	304	304	304

Notes:
Standard errors in parentheses.
LSDV is the least squares with dummy variables estimator.
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.

Before analyzing the whole distribution over the two sub-periods, it is worth noticing that in our estimates the U.S. has moved from second place in 1960–80 to the leading position in 1985–2003, and that few countries have obtained remarkable positive changes of rank—among them, South Korea (+27 positions), Singapore (+25), Taiwan (+23), Hong Kong (+19), and Thailand (+18). Notice that these are also the countries which 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 in achieving fast GDP per capita growth.

With regard to other characteristics of whole cross-country TFP distributions, 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 sub-periods (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 (dashed line) and subsequent TFP levels (solid line). 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.[31]

[31]For instance, Feyrer (2008) 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.

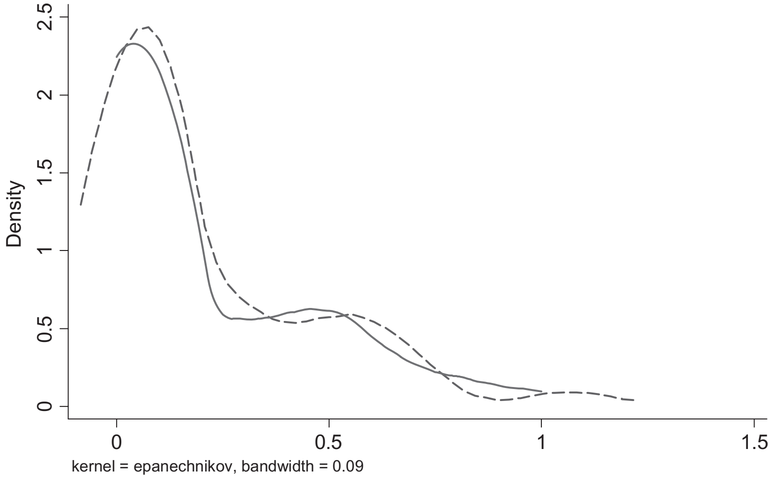

Figure 1. Distribution of TFP Levels

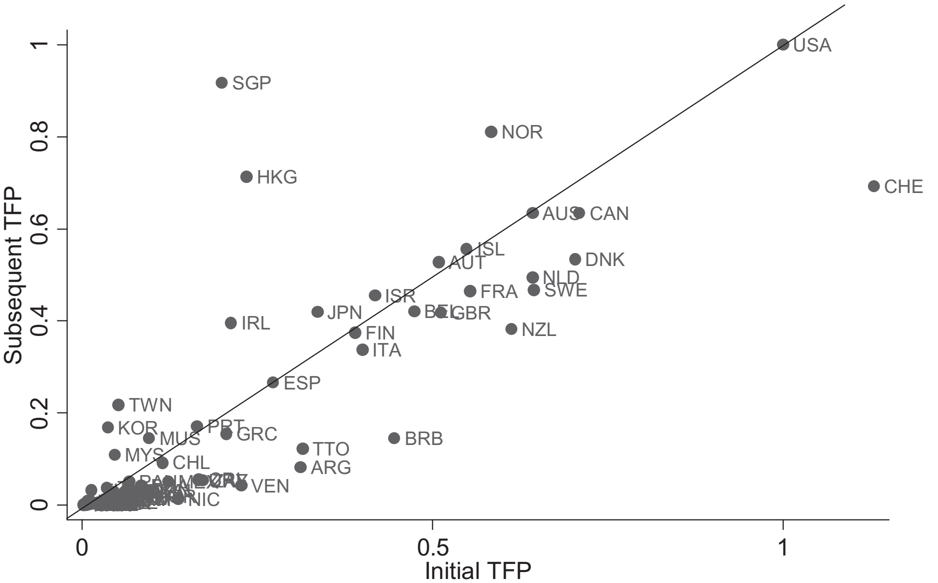

Figure 2. Two Periods TFP Estimates

As 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° line shows the locus where each country's relative (to U.S.) TFP level would be time-invariant. Since most countries are below the 45° line, they have clearly underperformed with respect to the U.S. in terms of TFP growth. Only seven countries seems to be significantly improving on the U.S.'s performance—namely, South Korea, Taiwan, Singapore, Hong Kong, Thailand, Ireland, and Malaysia. For a few other countries, the initial gap decreases, but far less significantly.[32]

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 LSDV estimates of $\tilde{TFP}_i$.

5. Technology Convergence and the Role of Human Capital

In Sections 3 and 4 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. In particular, it is possible that equation (11) does not represent the appropriate framework to investigate the main role of human capital within the growth process. Following Aghion and Howitt (2009), we distinguish two different approaches that analyze the link between growth and education: the Lucas approach, and the Nelson and Phelps approach. The Lucas approach is mainly characterized by assuming that human capital enters a growth model as an additional input in a standard Cobb–Douglas production function.[33] Conversely, the Nelson–Phelps approach to technology diffusion focuses on the hypothesis that the crucial role played by human capital in growth is an indirect one. 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 own technology level and the world technology frontier (or the technology adopted in a leader country).[34]

In the following we turn to the analysis of the direct relationship between TFP growth and human capital in our dataset using specifications alternative to equation (11) and based on Nelson and Phelps. Table 4 shows the results of several OLS cross-section regressions[35] with our measure of TFP growth rates (1960–2003 averages[36]) 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

[32]See also Figure A1 in the Appendix, where the relationship between TFP growth and initial levels is shown.

[33]This assumption lies behind equation (11) in Section 2, which is derived from Mankiw *et al.* (1992). This model assumes a standard labor-augmenting production function, namely $Y = K^{\alpha}H^{\beta}(AL)^{1-\alpha-\beta}$.

[34]With respect to the role of human capital as a direct input of a standard production function, Nelson and Phelps (1966) expressed the following well-known, skeptical viewpoint: "Our view suggests that the usual, straightforward insertion of some index of educational attainment in the production function may constitute a gross misspecification of the relation between education and the dynamics of production" (p. 75). In their view, the unconvincing feature of the traditional "production function" models is that they imply positive "payoffs" even when technology is stationary. To contrast this view, Nelson and Phelps develop two models (including the one on technology diffusion) based on an alternative formulation in which "education has a positive payoff only if the technology is always improving" (p. 70).

[35]All results in Tables 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.

[36]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. See also Hojo (2003).

TABLE 4

TFP Convergence, Average Years of Education and Social Infrastructure

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

	1	2	3	4	5	6	7	8
Human capital	0.009		0.016	0.017	0.009	0.009	0.01	0.009
	(0.002)		(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Initial TFP		0.055	–0.075		–0.155	–0.115		
		(0.016)	(0.033)		(0.038)	(0.029)		
HK*TFP				–0.010			–0.015	–0.010
				(0.004)			(0.004)	(0.003)
GADP					0.210		0.174	
					(0.035)		(0.032)	
GADP & openness						0.137		0.063
						(0.019)		(0.014)
R^2	0.26	0.09	0.31	0.33	0.54	0.55	0.51	0.47
Obs	73	73	73	73	73	73	73	73

Notes:
Robust standard errors in parentheses.
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 40.

this section the sample is reduced from 76 to 73 countries.[37] In all the regressions the human capital index, H_i, is defined as the average value of our initial sub-period, 1960–80.[38] The use of the value of our initial sub-period should control for likely endogeneity problems of our human capital indicator. Nevertheless, all our regressions have also been replicated using the 1960 human capital stocks to better control for endogeneity; our results did not change significantly.[39]

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

$$GRTFP_i = \psi_o + \psi_1 T\tilde{F}P_{i,1} + \psi_2 H_i + \varepsilon_i \tag{13}$$

where the dependent variable represents the annual average 1960–2003 growth rate of relative TFP, $T\tilde{F}P_{i,1}$ is the initial level of relative TFP, and H_i is, as said above, the stock of human capital in the population. Unlike standard GDP convergence analysis, equation (13) is broadly consistent with 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

[37]We are excluding Lesotho, Mozambique, and Nepal. For these countries we could not find data for social infrastructure, additional variables used in this analysis.

[38]As before, we use average years of schooling of the population over 15 years of age (Barro and Lee, 2000).

[39]These results are available upon request. We favor the use of the average 1960–80 values because during the first sub-period many countries went through rapid increases in education attainments.

convergence in which the conditioning factor is H: as a consequence, in cross-country growth regressions $\tilde{TFP}_{i,1}$ is expected to exhibit a significant inverse relation with $GRTFP_i$, and H_i a positive one.[40]

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 4). 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) significantly extend 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.[41]

The Benhabib and Spiegel (2005) extension is based on a "logistic" model of technology diffusion (see below). This model allows us to answer two 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 into two different clubs (converging versus 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 U.S., 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.

[40]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.

[41]The idea of a cross-country convergence mechanism conditional on human capital exceeding a certain threshold can also be found in Tamura (1996). This paper stresses the importance of the link between fertility rates and human capital investments of parents in their children and show the possibility of two development regimes, a Malthusian regime of high fertility and no human capital investment, and a modern growth regime of low fertility and rising human capital. A similar demographic transition pattern has been also described in Tamura (2006).

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.

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

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

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^*. Whenever this condition is not met, divergence will occur because too small human capital stocks do not allow 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:

$$GRTFP_i = \zeta_0 + \zeta_1 H_i - \zeta_2 [H_i \cdot T\tilde{F}P_{i,1}] + \varepsilon_i \tag{16}$$

where $\zeta_1 = (g + c)$ and $\zeta_2 = c$. In this case, point estimates with $\hat{\zeta}_2 > \hat{\zeta}_1$ 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 $\hat{\zeta}_2 > \hat{\zeta}_1$, thus implying a plausible positive point estimate of g.

With regard to the existence of a critical value of H as defined by equation (15), our estimates imply that the value of average years of schooling of the population over 15 years of age for the first sub-period (1960–80) under which countries would diverge in TFP from the leader is 0.89. Within our panel of countries, this value is extremely low: only Mali and Niger are below this human capital threshold, while leader countries have an average of approximately 10 years of schooling.[42] 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

[42]In particular, in the Barro and Lee (2000) dataset, the U.S. shows 9.7 average years of schooling of the population over 15 years of age. Conversely, Benhabib and Spiegel (2005) find that 27 of 75 countries were below their estimated threshold of H in 1960, even if the number of countries below the threshold decreases in time: using the 1995 values of H, only four countries were still below the estimated critical value.

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).[43] 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).[44] 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 (Guiso, 2007; Tabellini, 2008).

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, 2008).[45] As 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).[46]

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

As a final robustness check we have replicated the analysis of Table 4 using an alternative dataset built by Baier *et al.* (2006). This study provide alternative measures of TFP and human capital. Results obtained estimating Models 1–8 with the same sample of countries are almost identical. The only difference is provided

[43]See also Acemoglu *et al.* (2001), Parente and Prescott (1999), and Tabellini (2008).

[44]One channel linking the quality of institutions to growth performance has been recently assessed in Jerzmanowski (2006). While most countries go through periods of high growth, good institutions are needed to allow a country stay longer in a favorable growth regime. The lack of good institutions makes those episodes persistent.

[45]See the *International Risk Guide* compiled by Political Risk Services. GADP (government anti-diversion policies) is formed by the average of five categories: (i) corruption; (ii) risk of expropriation; (iii) government repudiation, as measures of the government as a potential diverter for private investment; (iv) law and order; and (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.

[46]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.

by results of Model 2: using the alternative dataset the initial TFP variable is also negative and significant in this specification.[47]

In sum, the broad set of results shown in this section yields evidence in favor of the hypothesis that human capital 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 be valid for nearly all countries in our panel, and to be robust to different model specifications and to the inclusion of various indexes of social infrastructure.

It also suggests that the influence exerted by human capital on TFP growth is independent of a country's institutional quality. This result is in contrast with the idea that human capital is an outcome of a country's social infrastructure, and therefore should not be regarded as an independent determinant of productivity (Hall and Jones, 1999). It is also in contrast to 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).

Our evidence of a possible 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 plays a second, less direct role in TFP growth through the influence exerted on social infrastructure.[48]

6. Stages of Developments and Different Educational Attainments

Finally, we run our cross-country regressions on $GRTFP_i$ using equation (13) again, but decomposing total schooling into three components: average years of primary, secondary, and tertiary schooling.[49] Horowitz *et al.* (2009) suggest that failing to distinguish among the different levels of education ignores the hierarchical nature and the qualitative distinctiveness of the different levels of human capital stocks and produces biased results in empirical growth analysis. Furthermore, recent catch-up models that can be classified within the Nelson and Phelps approach briefly described in the previous section emphasize how productivity growth is the result of both imitation of frontier technology and innovation of technology, and suggest that these two distinct processes may require different types of skills (Acemoglu *et al.*, 2006; Vandenbussche *et al.*, 2006; Jerzmanowski,

[47]These results are available upon request. In Baier *et al.* (2006), TFP and human capital data are roughly decadal. To replicate the analysis we have used the 1960 and 2000 observations. Moreover, the cross-section includes 71 countries since Iceland and Barbados are missing.

[48]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.

[49]Differently from Horowitz *et al.* (2009), who introduce as measures of human capital the fraction of the population that attained the different levels of education, we include in our regression analysis 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
Obs	73	73	73	21	52

Notes:

Robust standard errors in parentheses.

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 also footnote 40.

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 44.

2007). In particular, since innovation (or R&D) activities are certainly influenced by higher levels of education while imitation may be performed by labor forces with lower levels of skills, we expect for each economy a different role on TFP growth for different levels of education depending on its proximity to the technological frontier. The closer an economy is to the frontier the more effective higher levels of education will be for growth. Conversely, for less developed economies, a lower level of education would have a higher productivity and growth enhancing effect than "high brow" education. Since the sample is formed by both developed and less developed countries we may then expect the presence of parameter heterogeneity in our human capital coefficients.

Table 5 shows how equation (13)[50] performs when we decompose human capital in all three levels of education. We find that only the lower levels of schooling seem 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 of 21

[50]We exclude from this analysis the logistic specification since it has previously produced implausible results.

high-tech countries,[51] whose initial level of relative TFP is greater than 0.3; in Model 5 we do the same for a sample formed by the 52 remaining low-tech countries. With regard to 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 and 0.4.

Our estimates of Models 4 and 5 show that for advanced countries only tertiary education 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 a cut-off value of 0.4 instead of 0.3, implying a smaller group of high-tech economies.[52] To sum up, while results are indicative 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 labor force than imitation.

7. 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 U.S., 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.

With regard to 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),

[51]These are defined by countries with an 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, the U.K., and U.S.

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

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 to previously reported evidence, we find little evidence in favor of this hypothesis, since in our results even very low levels 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 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 with the principal gains from education for laggard countries coming from investing in lower levels of education.

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.

Appendix

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

TABLE A1 (*continued*)

Countries	Rank with GDP	Rank with LSDV	Rank with KIVIET	Rank with GMM–AB1
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
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 1960–80 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
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

TABLE A2 (*continued*)

Countries	Relative TFP Levels 1960–80	Ranking 1960–80	Relative TFP Levels 1985–2003	Ranking 1985–2003	Change of Rank
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

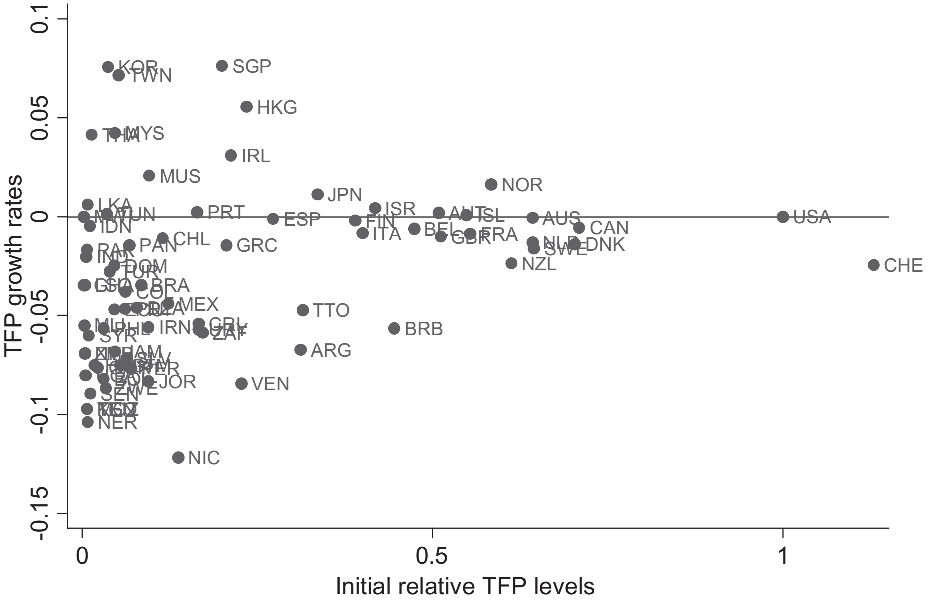

Figure A1. TFP Growth Versus Initial Levels

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