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Closing the Technology Gap?

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Abstract

This paper focuses on the dimensions shaping the dynamics of technology. We present a model where the knowledge stock of a country grows over time as a function of three main factors: its innovation intensity, its technological infrastructures and its human capital. The latter two variables contribute to determine the absorptive capacity of a country as well as its innovative ability. Based on this theoretical framework, we carry out an empirical analysis that investigates the dynamics of technology in a large sample of developed and developing economies in the last two-decade period, and studies its relationships with the growth of income per capita in a dynamic panel model setting. The results indicate that the cross-country distributions of technological infrastructures and human capital have experienced a process of convergence, whereas the innovative intensity is characterized by increasing polarization between rich and poor economies. Thus, while the conditions for catching up have generally improved, the increasing innovation gap represents a major factor behind the observed differences in income per capita.

Keywords: Growth and development; technology gap; absorptive capacity; innovation; polarization; twin-peaks

JEL classification: O11, O33, O40

1. Introduction

A recent body of research in applied growth theory focuses on the issue of cross-country heterogeneity, and points out the great diversity of countries' characteristics and growth behaviour. The study of the variety of economic growth patterns across countries does now constitute a central research theme in growth empirics (Temple, 1999; Islam, 2003; Durlauf et al., 2005).

One strand of research in this tradition has in particular studied the evolution of the world income distribution and pointed out the existence of increasing polarization between the club of rich and the group of poor countries (Quah, 1996a; 1996b; 1996c; 1997). Empirical analyses investigating the so-called *emerging twin-peaks* in the world distribution of income have flourished rapidly in the last decade (Bianchi, 1997; Jones, 1997; Paap and van Dijk, 1998; Anderson, 2004).

What are the factors that may explain these empirical findings on clustering and income polarization? One major explanation, recently proposed by growth models in the *technology-gap* (or *distance-to-frontier*) tradition, points to innovation and the international diffusion of new technologies as the possible sources of income polarization and convergence clubs (Papageorgiou, 2002; Howitt and Mayer-Foulkes, 2005; Stokke, 2008).¹ More specifically, technology-gap models argue that two main dimensions determine the ability of a country to catch up. The first is its *absorptive capacity*, i.e. its ability to imitate foreign advanced technologies. The second is its *innovative capability*, namely the extent to which the country is able to produce new advanced knowledge.

While the importance of absorptive capacity and innovative ability for the growth process is widely acknowledged in modelling exercises, the empirical literature has not yet achieved a systematic understanding of how these two dimensions evolve over time, and how the technological dynamics is related to the evolution of the world distribution of income.

This paper carries out an empirical study that has two interrelated objectives. First, it investigates the dynamics of technology by focusing on the evolution of innovative activities and absorptive capacity, considering a large sample of countries in the last two-decade period. Secondly, it studies the link between technological and economic dynamics. By analysing the evolution of the world distribution of technological capabilities, we may thus investigate the extent to which technology is an important factor to explain the pattern of increasing income polarization and emerging twin-peaks, and identify the technology dimensions that are more closely related to the dynamics of GDP per capita.

We first present a simple model where the technology dynamics of a country depends on three main factors: its innovative intensity, its human capital and its technological infrastructures. The latter two factors are assumed to shape the dynamics of both, the country's absorptive capacity and the productivity of its R&D sector. The model is therefore rooted in the technology-gap tradition. However, differently from the standard formulation where absorptive capacity only depends on human capital (Benhabib and Spiegel, 1994; 2005), our model adds a new dimension by pointing out the importance of technological infrastructures for the catching up process.

Our empirical analysis of this model proceeds in three steps. First, we employ a set of indicators to measure the three technology dimensions pointed out by the model, and carry out a hierarchical cluster analysis that explores the existence of various groups of countries differing in terms of their levels of technological development. The results of the cluster analysis show the existence of three technology clubs with strikingly different technological characteristics and, relatedly, two large technology gaps separating these country groups. Secondly, we shift the focus to the study of the dynamics of these technology clubs, and make use of four different notions of technological convergence. Two of them are the well-known concepts of β -convergence and σ -convergence. The other two are new notions of

convergence that we put forward in order to refine these standard definitions. The first refinement (*Q-convergence*) is based on the estimation of quantile regressions for different percentiles of the conditional distributions of the technology growth rate, while the second (*cluster convergence*) is based on the analysis of the dynamics of the technology gaps over time. Finally, the third step of our empirical analysis is to investigate the implications of this technology dynamics for the growth of GDP per capita, and to estimate our technology-gap model in a dynamic panel model setting for the period 1970-2000.

The empirical results indicate that the cross-country distributions of human capital and technological infrastructures have experienced a process of convergence, while the evolution of innovative intensity is characterized by increasing polarization between rich and poor countries. Thus, while the conditions for catching up have generally improved, the increasing innovation gap represents a major factor behind the observed differences in income per capita.

2. The model

The simple model presented in this section provides the theoretical framework of the paper. It focuses on technology as a major growth factor, and analyses the channels through which the dynamics of technology fosters the dynamics of income per capita. The growth of the knowledge stock of country i (A_i) is the sum of two components, knowledge creation (KC_i) and knowledge imitation (KI_i):

$$\Delta A_i/A_i = KC_i + KI_i \tag{1}$$

The knowledge imitation term is driven by the dynamics of the international diffusion of technologies. In line with previous technology-gap models (e.g. Benhabib and Spiegel, 1994 and 2005; Papageorgiou, 2002; Galor, 2005; Howitt and Mayer-Foulkes, 2005; Stokke, 2008), we assume that knowledge imitation (KI_i) depends on two factors: the technological distance from the frontier (GAP_i), which provides opportunities for catching up through the imitation of foreign advanced technologies, and the absorptive capacity (δ_i), which affects the extent to which these imitation opportunities are exploited by each country:

$$KI_i = GAP_i^\beta \cdot \delta_i \quad (2)$$

The next equation endogeneizes absorptive capacity. The latter is assumed to depend on two related factors, human capital (HK_i) and technological infrastructures (TI_i):

$$\delta_i = TI_i^{\delta_1} \cdot HK_i^{\delta_2} \quad (3)$$

The human capital component (HK_i) is the one that is commonly emphasized in technology-gap growth models. Besides, we argue that a second important factor affecting the absorptive capacity of a nation is its level of technological infrastructures (TI_i). This is technology that is embodied in the infrastructures that support productive activities and that enables the communication between economic agents. When new technologies are produced, they are progressively used to improve the infrastructures of the economy, and this has the effect of increasing the efficiency of production in all industrial sectors that make use of these infrastructures.² Technological infrastructures represent therefore a crucial factor affecting the absorptive capacity of a country. Human skills would in fact be

useless without the possibility of agents to communicate with each other and without the support of a well-functioning network of industrial infrastructure.³

The other component affecting the growth of the knowledge stock of country i (A_i) is represented by the knowledge creation term (KC_i). We model this as:

$$KC_i = INN_i^\alpha \cdot \theta_i \quad (4)$$

The first term in this equation (INN_i) symbolizes the innovative intensity of a country. This refers to both, formalized R&D activities undertaken by profit-motivated firms as well as scientific activities carried out by the public research sector. The extent to which innovative activities do effectively lead to the creation of new advanced knowledge depends on the productivity of the research sector, represented by the second term of the equation (θ_i). We endogeneize the productivity of the R&D sector by means of the following formulation:

$$\theta_i = TI_i^{\theta_1} \cdot HK_i^{\theta_2} \quad (5)$$

Equation 5 assumes that the term θ_i depends on both human capital and technological infrastructures. This formulation argues that these two factors do not only have an impact on the ability of a country to imitate foreign advanced technologies by enhancing its absorptive capacity, but they are also important dimensions in the knowledge creation process (Cohen and Levinthal, 1989; Papageorgiou, 2002).

Taking logs of equations 2 and 4 and plugging them into 1, the growth of the knowledge stock of country i can be rewritten as:

$$\Delta A_i/A_i = \alpha \log INN_i + (\theta_1 + \delta_1) \log TI_i + (\theta_2 + \delta_2) \log HK_i + \beta \log GAP_i \quad (6)$$

Equation 6 highlights the four major factors determining the dynamics of the knowledge stock in our model. The first term is the intensity of the innovative effort undertaken by the country's R&D sector. The second is the level of technological infrastructures, which has an effect on both knowledge creation and imitation (measured by the parameters θ_1 and δ_1 respectively). The third term is the human capital level, which does also have an effect on both knowledge creation and imitation (parameters θ_2 and δ_2). Finally, the fourth term is the technology-gap, which provides a potential for exploiting foreign advanced technologies. In sum, equation 6 provides a rather general formulation that refines previous technology-gap models by adding technological infrastructures to human capital as the major factors affecting the related processes of knowledge imitation and production.⁴

We can now derive the implications of the knowledge stock dynamics for economic growth in a standard growth accounting framework. The aggregate production function (expressed in per worker term) is:

$$y_i = A_i \cdot k_i^\gamma \quad (7)$$

where y_i is the GDP per worker of country i , A_i is its knowledge stock and k_i is the level of physical capital per worker. The growth of GDP per worker over time is:

$$\Delta y_i / y_i = \Delta A_i / A_i + \gamma \Delta k_i / k_i \quad (8)$$

Since the second term represents the investment rate (INV_i), we rewrite equation 8 as:

$$\Delta y_i / y_i = \alpha \log INN_i + a \log TI_i + b \log HK_i + \beta \log GAP_i + \gamma INV_i \quad (9)$$

where $a = (\theta_1 + \delta_1)$ and $b = (\theta_2 + \delta_2)$. The first four terms represent the factors driving the growth of technological knowledge pointed out above, while the last one indicates the process of physical capital accumulation. This growth accounting equation constitutes the basic framework for the empirical analysis that will be presented in the following sections. Sections 3 and 4 will focus on the first three terms on the right-hand side of equation 9, in order to analyse the patterns and dynamics of technological change in the world economy in the last two- decade period. Section 5 will then consider the whole equation and explore the empirical relationship between the dynamics of technology and the growth of income per capita.

3. Data, indicators and descriptive analysis

The model presented in the previous section highlights three main dimensions of the process of technological accumulation: innovative intensity (INN), technological infrastructures (TI) and human capital (HK). This section presents a set of indicators and some descriptive evidence on these three technology dimensions. We consider a cross-country sample constituted by 131 developed and developing economies for the period 1985-2004.⁵ For each aspect, we make use of the following indicators.

Indicators of innovative intensity (INNOV):⁶

- *Patents*: Number of patents registered at the US Patent and Trademark Office per million people (source: USPTO, 2004).
- *Scientific articles*: Number of scientific and technical journal articles per million people (source: World Bank, 2006).

Indicators of (new and old) technological infrastructures (TI):

- *Internet penetration*: Number of Internet users per thousand people (source: World Bank, 2006).
- *Mobile telephony*: Number of mobile phone subscribers per thousand people (source: World Bank, 2006).
- *Fixed Telephony*: Number of telephone mainlines per thousand people (source: World Bank, 2006).
- *Electricity*: Number of kilowatt of electricity consumed per hour per capita (source: World Bank, 2006).

Indicators of (advanced and basic) human capital (HK):⁷

- *Tertiary enrolment ratio*: Share of tertiary students (source: World Bank, 2006).
- *Years of higher schooling*: Average number of years of higher education in the population over 15 (source: Barro and Lee, 2001).
- *Secondary enrolment ratio*: Share of secondary students (source: Barro and Lee, 2001).
- *Years of total schooling*: Average number of years of school completed in the population over 15 (source: Barro and Lee, 2001).
- *Primary enrolment ratio*: Share of primary students (source: Barro and Lee, 2001).
- *Literacy rate*: Percentage of people over 14 who can, with understanding, read and write a short, simple statement on their everyday life (source: World Bank, 2006).

The advantage of using a large number of indicators is that we are able to provide a more multifaceted description of countries' technological level than if we were using one single indirect measure such as their total factor productivity (TFP). This is particularly important

in a large sample that includes countries characterized by very different levels of technological and economic development.⁸ While the main interest of our empirical analysis is to investigate the *dynamics* of technology in this large sample of countries, it is useful to start by providing a general idea of the extent of cross-country differences in the *level* of technology.

We do this by means of a cluster analysis, whose purpose is to explore the existence of groups of countries characterized by different technological capabilities. The exercise follows a hierarchical cluster methodology, which is a clustering technique able to find out endogenously the most appropriate number of country groups. The main result of this exercise is that three well distinct *technology clubs* emerge robustly from the cluster analysis.⁹ The major characteristics of these country clubs are presented in table 1 and Appendix 1, and they are briefly described as follows.

Cluster 1: Advanced. This is the group of more technologically advanced countries, composed by a small set of industrialized economies: the traditional leaders, US and Japan, Continental and Northern European economies, and Western offshoots (Australia, Canada, Israel and New Zealand). Table 1 shows that at the beginning of the period the group is characterized by high innovative intensity (on average, around 62 patents and 644 scientific articles per million people), well-developed technological infrastructures (in terms of both old and new infrastructures), and high levels of basic and advanced education (over 42% tertiary enrolment ratio, more than 9 years of total schooling, and nearly 99% literacy rate).

Cluster 2: Followers. This is a larger group composed by around 70 countries. The core of this technology club is constituted by catching-up economies from Asia, the South of Europe, the Middle East and Latin America. Compared to the advanced cluster, this group shows a much lower innovative intensity. In fact, table 1 indicates that at the beginning of the period the innovation gap between the advanced and the followers group is quite huge

(nearly 16:1 for patents, 10:1 for articles). Over the period, the technological distance has gradually decreased, although the innovation gap *vis-à-vis* the economies in the advanced cluster does remain considerable. On the other hand, the technological distance between this second group and the more advanced one is significantly lower in terms of technological infrastructures and education levels, and the gap has significantly diminished during the last two decades.

Cluster 3: Marginalized. This is the largest group of countries, mainly constituted by large Asian economies plus many African countries. In terms of innovative intensity, this group is not only remarkably far from the technological frontier, but also quite distant from the follower countries in the second cluster. Table 1 shows in fact that at the beginning of the period the technological distance between the followers and the marginalized groups is around 273:1 in terms of patents and 19:1 for scientific articles. Regarding the indicators of technological infrastructures and human capital, the distance *vis-à-vis* the followers cluster at the beginning of the period is also remarkable, although the gap has gradually diminished during the period.

In short, this empirical description indicates that the first group is rich in terms of both innovative ability and absorptive capacity; the middle-income group has a lower ability to innovate; and the less developed group does also lag behind in terms of absorptive capacity. These results point out the existence of two large technology gaps. The first refers to the great distance that separates the group of followers from the technological frontier, particularly with respect to innovative activities. The second refers to the huge gap that separates the marginalized from the followers clubs, both in terms of innovative intensity and of infrastructures and human capital.

Table 1. Main characteristics of the three technology clubs, beginning (t_0) and end (t_1) of the period

		<i>Cluster 1: Advanced</i>		<i>Cluster 2: Followers</i>		<i>Cluster 3: Marginalized</i>	
		t_0	t_1	t_0	t_1	t_0	t_1
<i>INN</i>	<i>Patents</i>	61.89	116.12	3.90	9.16	0.01	0.02
	<i>Scientific articles</i>	644.8	791.4	67.6	110.4	3.6	5.3
<i>TI</i>	<i>Internet users</i>	51.9	613.8	4.7	225.1	0.0	32.1
	<i>Mobile telephony</i>	49.0	799.2	6.5	444.5	0.2	70.2
	<i>Fixed telephony</i>	429.4	597.1	123.7	262.7	8.3	38.2
	<i>Electricity</i>	9290.6	12107.9	2626.8	3672.9	223.7	395.8
<i>HK</i>	<i>Tertiary enrolment ratio</i>	42.2	66.5	24.4	40.8	4.2	8.2
	<i>Years of higher schooling</i>	0.46	0.75	0.17	0.40	0.03	0.08
	<i>Secondary enrolment ratio</i>	98.3	119.1	75.4	90.3	29.7	45.1
	<i>Years of total schooling</i>	9.3	10.4	6.1	7.1	2.5	3.5
	<i>Primary enrolment ratio</i>	5.63	5.87	4.04	4.64	1.95	2.81
	<i>Literacy rate</i>	98.5	98.9	91.3	94.3	51.6	63.3

Notes: The list of countries included in each cluster is reported in Appendix 1.

4. The dynamics of technology

How have these technology gaps evolved in the last two-decade period? This section considers this question by investigating the dynamics of technology over the period 1985-2004. In line with our theoretical framework, the three dimensions that we look at are innovative intensity (INN), technological infrastructures (TI) and human capital (HK). Since there exists no prior theory or model indicating how these three dimensions evolve over time, our analysis of technological dynamics follows a simple empirical strategy.

We carry out a standard analysis of (unconditional) convergence for each of these three factors, and study how their statistical distributions have evolved in the last two decades. For each dimension, a pattern of *convergence* would indicate that a process of technological catching up is in place, meaning that less developed economies have experienced a more rapid technological dynamics than industrialized countries. By contrast, a finding of *divergence* would indicate the presence of a cumulative mechanism that is leading to increasing disparities between rich and poor countries.¹⁰

The analysis proceeds by considering four different notions of convergence. Two of them, β -convergence and σ -convergence, are well known and widely used in applied growth theory. In addition, we put forward two new concepts of convergence, *Q-convergence* and *cluster convergence*, which represent refinements of the standard definitions, and which make it possible to shed new light on the evolution of the world distribution of technological activities.

4.1 β -convergence and Q-convergence

We start by considering the standard notion of β -convergence. For each of the three technology dimensions, the dependent variable is the (average annual) growth of

technology over the period 1985-2004, while the level of the same indicator at the beginning of the period is the only regressor. The cross-country regression model is:

$$\Delta A_i/A_i = \tau_A + \beta_A A_{i,0} + \varepsilon_i \quad (10)$$

where $\Delta A_i/A_i$ is the growth of each technology dimension (i.e. $\Delta HK_i/HK_i$; $\Delta TI_i/TI_i$; $\Delta INN_i/INN_i$) of country i over the period, and $A_{i,0}$ is the log of its level at the beginning of the period (i.e. $HK_{i,0}$; $TI_{i,0}$; $INN_{i,0}$). The parameter of interest in these regressions is β_A , which measures the speed of convergence for each of the three dimensions of technology (i.e. β_{HK} , β_{TI} and β_{INN}).

The first column of table 2 reports these estimated β coefficients, which turn out to be negative in all the regressions. All indicators suggest therefore a pattern of β -convergence in technology. The speed of convergence is rapid for ICTs infrastructures (Internet: 6,6%; mobile telephony: 6%), less so for the indicators of primary and secondary education levels (around 2%), and significantly slower for innovative activities, traditional infrastructures and advanced education (all lower than 1%).

The notion of β -convergence provides a simple and intuitive idea of the growth behaviour of the average of the distribution of the technology indicators, but it tells nothing about the evolution of the whole distribution over time. As such, it is a necessary but not sufficient condition for convergence (Quah, 1993). It is thus important to look at the convergence pattern also from a different perspective.

We thus propose a refinement of the notion of β -convergence and define it *Q-convergence*.

The idea is to study β -convergence by estimating a set of quantile regressions instead of one single ordinary least squares (OLS) regression as customary in the convergence literature.

While an OLS regression estimates the conditional mean function, providing an idea of the

behaviour of the average of the distribution, a quantile regression estimates a conditional quantile (percentile) function, and thus enables an analysis of the behaviour of different parts of the distribution, including the tails (Koenker and Bassett, 1978; Koenker and Hallock, 2001).

In our study of cross-country technological dynamics, Q-convergence is investigated by running a set of j quantile regressions for each of the three dimensions of technology:

$$(\Delta A_i/A_i)^j = \tau_A^j + \beta_{AA} A_{i,0}^j + \varepsilon_i^j \quad (11)$$

where j is the j^{th} quantile of the technology dimension (HK, TI and INN, respectively), i.e. the j^{th} percentile of the conditional growth distribution of each technology indicator. In other words, for each indicator, we estimate j cross-country regressions, each of which measures the speed of β -convergence in technology at a different quantile of the growth distribution. Q-convergence is investigated by looking at the vector $[\beta^j]$, where the j different components of the vector are the coefficients β^j estimated from the quantile regressions specified above. By looking at different percentiles of the conditional growth distribution, Q-convergence provides a more complete characterization of the dynamics of technological convergence than the simple notion of β -convergence is able to do.

The results for our technology indicators are presented on the right-hand side of table 2, where, for each indicator, we report the estimated vector $[\beta^j]$ corresponding to the 20th, 40th, 60th and 80th quantiles of its conditional growth distribution. For all of the indicators, the results show that the β coefficient differs substantially across the distribution. In general terms, the speed of convergence is much greater (smaller) at upper (lower) quantiles. Besides, for the variables measuring innovative intensity (patents and scientific articles) the

estimated β coefficient has a positive sign in correspondence to the lower part of the distribution, indicating technological divergence.

The interpretation of this finding is the following. The regressions that refer to the upper quantiles of the conditional growth distribution focus on the countries that have been particularly dynamic in the period, i.e. those economies whose growth rate of technology has been faster than it could have been expected based on their initial level of technology. These regressions investigate therefore the convergence hypothesis by focusing on the well-performing countries at different levels of development, including the fast-growing developing economies (e.g. China), the industrialized countries catching up with the technological frontier (e.g. Asian NICs), and the most dynamic leaders. Analogously, the regressions referring to the lower quantiles of the conditional growth distribution analyse the convergence hypothesis for the low-performing countries in the sample, i.e. for the economies whose technological performance has been more sluggish than it could have been expected based on their income level at the beginning of the period, including marginalized economies falling behind as well as slow-growing industrialized and rich countries.

The results presented in table 2 indicate that when we focus on the upper quantiles of the conditional growth distribution we observe a rapid process of technological convergence, meaning that a few fast-growing developing economies have been able to develop more rapidly than the other (richer) well-performing countries in the sample. This suggests that a process of technological catching up is at stake. However, the key point is that technological convergence is by no means a characterizing feature of the whole sample. When we focus on the lower quantiles of the distribution, low-performing poor countries have in some cases not been able to develop their technological capabilities more rapidly than industrialized and rich low-performing economies. This is particularly evident for the

indicators of innovative intensity, where we indeed observe technological divergence. This suggests that, in this part of the conditional growth distribution, a process of increasing disparities between developed and less developed economies has been at stake.

Table 2. β -convergence and Q -convergence in technology, 1985-2004

		β -convergence	Q -convergence			
			20 th quantile	40 th quantile	60 th quantile	80 th quantile
INN	<i>Patents</i>	-0.26%	+0.19%	-0.15%	-0.42%	-0.54%
	<i>Scientific articles</i>	-0.06%	+0.65%	+0.38%	-0.22%	-0.56%
TI	<i>Internet users</i>	-6.60%	-5.50%	-6.43%	-7.04%	-7.31%
	<i>Mobile telephony</i>	-5.97%	-5.08%	-5.84%	-6.77%	-8.00%
	<i>Fixed telephony</i>	-0.80%	-0.20%	-0.77%	-1.20%	-1.82%
	<i>Electricity</i>	-0.33%	-0.36%	-0.19%	-0.28%	-0.38%
HK	<i>Tertiary enrolment ratio</i>	-0.72%	0.00%	-0.75%	-0.84%	-1.43%
	<i>Years of higher schooling</i>	-0.87%	-0.49%	-0.86%	-1.15%	-1.51%
	<i>Secondary enrolment ratio</i>	-2.00%	-1.56%	-2.22%	-2.47%	-2.77%
	<i>Years of total schooling</i>	-1.03%	0.00%	-1.02%	-1.19%	-1.45%
	<i>Primary enrolment ratio</i>	-1.60%	-1.28%	-1.60%	-1.72%	-1.79%
	<i>Literacy rate</i>	-2.12%	-1.61%	-1.89%	-2.44%	-3.03%

Notes: The first column reports the β -convergence coefficient estimated from OLS regression 10. The other four columns report the coefficients of convergence β^j estimated from quantile regressions 11, where j is the j th percentile of the conditional distribution of the growth rate of each technology indicator.

4.2 σ -convergence and cluster convergence

The idea of σ -convergence is to study whether the dispersion of a target variable has increased or decreased over time, thus providing a synthetic measure of the dynamics of the variability of its distribution.¹¹ Table 3 presents the results of the analysis of σ -convergence for our technology indicators. The first two columns report the coefficient of variation of each indicator at the beginning and at the end of the period, and the third column presents its rate of change over the period, which represents a synthetic measure of σ -convergence. The table indicates that all of the technology variables are characterised by decreasing dispersion over time. The speed of σ -convergence is particularly rapid for the indicators of ICTs infrastructures (Internet and mobile telephony, more than 50%). The variables measuring traditional infrastructures, education levels and innovative activities have also experienced a decrease in the cross-country dispersion. However, the coefficient of variation shows that the variability across countries is still large at the end of the period, particularly in terms of innovative intensity. These σ -convergence results are in line with the findings of the β - and Q-convergence analysis presented above, and suggest that, in general terms, the evolution of the world distribution of technological activities has been characterized by an overall pattern of convergence over the last two decades, although different groups of countries have experienced distinct dynamics of technological change. In order to look more specifically at the behaviour and relative dynamics of different groups of countries, we propose a second refinement of the convergence concept.

The concept of *cluster convergence* that we introduce here develops naturally from the results of the cluster analysis presented in section 3, which have pointed out the existence of three technology clubs. A general definition of cluster convergence may be the following: *Given a statistical distribution partitioned into k clusters, cluster convergence arises when the centre of a group gets closer to the centre of the upper cluster over time.* For our

technology clubs, we therefore observe cluster convergence if the centre of the followers (marginalized) cluster has come closer to the centre of the advanced (followers) club, i.e. if the technological distance between them has diminished over the period. This notion refines the one of σ -convergence because it enables to investigate whether the observed decrease in the dispersion of the technology indicators has been determined by a rapid catching up of the followers *vis-à-vis* the technological frontier, or by a rapid catching up of the marginalized *vis-à-vis* the followers, or by both of them.

The results of the cluster convergence analysis are presented on the right-hand side of table 3. The table shows that the club of followers has on average decreased its technological distance from the advanced group for all the dimensions of technology considered here. This catching up process has been remarkably rapid in terms of Internet users and mobile telephony, reflecting the worldwide diffusion of ICTs. It has also been quite dynamic with respect to innovative activities, which is precisely the aspect where the technology gap between the followers and the advanced clubs was more evident at the beginning of the period (see section 3).

When we turn the attention to the dynamics of the marginalized *vis-à-vis* the followers club, however, the picture is different. Here, convergence is rapid in terms of ICTs infrastructures, and less so for the indicators of traditional infrastructures (electricity) and education. On the other hand, the innovation gap between the marginalized and the followers clubs has significantly increased (patents: +35.7%; scientific articles: +10.5%), indicating that the group of marginalized economies has not yet been able to intensify its innovative efforts, while the other two groups have been much more dynamic in this respect. This is in line with the finding of the Q-convergence analysis, which suggests the existence of divergence and increasing polarization at the lower quantiles of the distributions of these two indicators.¹²

Table 3. σ -convergence and cluster convergence in technology, 1985-2004

		σ -convergence			Cluster convergence	
		Coefficient of variation in t_0	Coefficient of variation in t_1	Rate of change	Advanced vs. Followers	Followers vs. Marginalized
INN	<i>Patents</i>	3.08	2.65	-13.8%	-20.1%	+35.7%
	<i>Scientific articles</i>	2.14	1.93	-9.8%	-24.8%	+10.5%
TI	<i>Internet users</i>	2.66	1.20	-54.9%	-75.4%	-92.6%
	<i>Mobile telephony</i>	2.25	1.04	-53.6%	-76.2%	-79.6%
	<i>Fixed telephony</i>	1.36	1.05	-22.5%	-34.5%	-54.1%
	<i>Electricity</i>	1.46	1.41	-3.8%	-6.8%	-21.0%
HK	<i>Tertiary enrolment ratio</i>	0.89	0.80	-9.9%	-5.7%	-15.1%
	<i>Years of higher schooling</i>	1.18	0.90	-23.5%	-31.6%	-7.4%
	<i>Secondary enrolment ratio</i>	0.56	0.44	-21.0%	+1.3%	-21.0%
	<i>Years of total schooling</i>	0.55	0.47	-15.1%	-3.0%	-16.6%
	<i>Primary enrolment ratio</i>	0.53	0.39	-26.6%	-9.1%	-20.3%
	<i>Literacy rate</i>	0.33	0.26	-23.6%	-2.8%	-15.7%

Notes: The first two columns report the coefficient of variation at the beginning and at the end of the period respectively (the coefficient of variation is defined as the standard deviation divided by the mean). The third column shows the rate of change of the coefficient of variation over time, which is a measure of σ -convergence in the period 1985-2004. The fourth (fifth) column reports the rate of change of the technology gap between the advanced (followers) and followers (marginalized) clubs. These rates of change represent our measure of cluster convergence, and have been calculated by comparing the levels of the technology gaps at the beginning and at the end of the period.

5. The link between technological and income dynamics

The findings of the previous section indicate that the group of indicators that have experienced the most rapid pace of technological convergence are those measuring ICT-related infrastructures, i.e. Internet and mobile telephony, while more traditional infrastructures (electricity and fixed telephony) have been converging at a much slower pace. The world distribution of human capital is also characterized by an overall process of convergence, although the speed of convergence has been faster for the indicators of basic education (primary and secondary schooling) than for those measuring tertiary education. By contrast, the other important dimension of technology outlined in the model, the innovative intensity, has experienced a different dynamics, since middle-income countries have been able to partly close the technology gap, while the group of less developed economies has not. With respect to this dimension, we therefore observe increasing polarization between rich and poor countries, and the progressive catching up (or vanishing) of the middle-income group.

This dynamics resembles closely what Quah (1996a; 1996b; 1996c; 1997) called *emerging twin-peaks*. Quah's well-known empirical result refers however to the evolution of the cross-country distribution of income, rather than the dynamics of technology. This leads to pose one relevant question: what is the relationship between the dynamics of technology and the growth of income, and what are the dimensions of technology that are most closely related to economic growth? We analyse this question by means of two conclusive exercises.

The first is to repeat the convergence analysis undertaken in the previous section by focusing on the dynamics of GDP per capita in the period 1985-2004. Tables 4 and 5 present the results of the four convergence tests that have been used to analyse technological convergence in section 4, namely the β -, Q-, σ - and cluster-convergence tests.

The results indicate that, differently from most of the technology indicators, income per capita has been characterized by an overall pattern of divergence, where poor countries have not in general been able to grow more rapidly than richer economies (see table 4). In addition, the cross-country variability of the distribution has increased by about 9%, and this has mainly been due to the increasing income gap between marginalized economies and the rest of the world (see table 5). These findings show that, even when we focus on a more recent period than Quah did, the *emerging twin-peaks* pattern is still evident.

The key point for our analysis is therefore that the evolution of the world income distribution in the last two decades has followed a pattern very similar to that experienced by the dynamics of innovative activities, since both of them are characterized by increasing polarization between rich and poor countries.¹³

Table 4. β -convergence and Q -convergence tests for the GDP per capita, 1985-2004

β -convergence		Q -convergence			
	20 th quantile	40 th quantile	60 th quantile	80 th quantile	
	+0.19%	+0.62%	+0.41%	+0.19%	-0.34%

Table 5. σ -convergence and cluster convergence tests for the GDP per capita, 1985-2004

σ -convergence			Cluster convergence	
Coefficient of variation in t_0	Coefficient of variation in t_1	Rate of change	Advanced vs. Followers	Followers vs. Marginalized
0.99	1.08	+8.8%	-2.9%	+9.4%

The second exercise that we carry out in order to study the relationship between the dynamics of technology and the growth of GDP per capita is to analyse the link between the former and the latter in a panel model setting. We do this by estimating equation 9 (see section 2), which decomposes the growth of GDP per capita into the sum of the dynamics of technology and the rate of physical capital accumulation. The empirical version of this growth accounting equation is:¹⁴

$$\Delta y_i / y_i = \gamma \text{INV}_i + \alpha \log \text{INN}_i + a \log \text{TI}_i + b \log \text{HK}_i + \beta \log y_i - \beta \log y_L \quad (12)$$

where y_L is the GDP per capita of the leader country (hence the last two terms of the equation correspond to the term $\log \text{GAP}_i$ of equation 9). In a panel data setting, where a full set of country-specific and time-specific effects can be added to the set of explanatory variables, equation 12 can be written as:

$$\log y_{i,t} = (1 + \beta) \log y_{i,t-1} + \gamma \text{INV}_{i,t-1} + \alpha \log \text{INN}_{i,t-1} + a \log \text{TI}_{i,t-1} + b \log \text{HK}_{i,t-1} + \eta_i + \mu_t - \beta \log y_{L,t-1} + \varepsilon_{i,t} \quad (13)$$

where η_i represents the set of country-specific effects and μ_t is the time-specific component. We may also define $(\mu_t - \beta \log y_{L,t-1}) = \rho_t$ since these two terms are invariant across countries and can both be accounted for in the set of time dummies. By first differencing equation 13, we eliminate the country-specific effect η_i and obtain the growth equation specified in first differences:

$$\Delta \log y_{i,t} = (1 + \beta) \Delta \log y_{i,t-1} + \gamma \Delta \text{INV}_{i,t-1} + \alpha \Delta \log \text{INN}_{i,t-1} + a \Delta \log \text{TI}_{i,t-1} + b \Delta \log \text{HK}_{i,t-1} + \Delta \rho_t + \Delta \varepsilon_{i,t} \quad (14)$$

Equation 14 is the empirical counterpart (in panel form) of the reduced form equation of our technology-gap model (see equation 9 in section 2). In line with our theoretical framework, the dynamic panel specification relates the growth of GDP per capita of country i to the dynamics of the following main explanatory variables: (1) the lagged level of the dependent variable¹⁵; (2) the investment rate; (3) the intensity of innovative activities; (4) the level of technological infrastructures; (5) the human capital level. As presented in section 2, the last two factors are assumed to have an impact on both the absorptive capacity and the productivity of the R&D sector, thus affecting at the same time the imitation capability and the innovation ability of a country.¹⁶ All technology-related variables are measured by means of the indicators presented and analysed in sections 3 and 4. The investment indicator is measured as capital investment as a share of GDP per capita, and the latter is in log form (both variables are from the Penn-World Tables, version 6.1).

As compared to the standard OLS cross-country regression framework, the dynamic panel specification presents two advantages. First, by including a full set of country-specific effects among the regressors, the fixed-effects specification overcomes the omitted variable bias that arises in the presence of cross-country heterogeneity (Islam, 1995). Secondly, the dynamic model specification takes into account the possible endogeneity of the explanatory variables (Caselli et al., 1996). A common strategy in the panel approach to growth empirics is to employ Arellano and Bond (1991) GMM estimator, which treats all the regressors as endogenous variables and uses their lagged levels as instruments for the lagged first differences. This is the method we use to estimate equation 14. As customary in the panel growth approach, all the variables are averages over 5-year periods. Since one of the variables (scientific articles) is only available for a shorter time span, we consider two

different estimation periods. The longer one is 1970-2000 (composed of six 5-year periods), whereas the shorter time span refers to 1985-2000 (three 5-year periods).¹⁷

Table 6 presents the estimation results. The tests reported in the lower part of the table confirm the validity of the instruments (Sargan test) and the absence of second-order autocorrelation. The bottom of table presents the results of three panel unit root tests (Levin-Lin-Chu, Im-Pesaran-Shin, and Fisher), which all reject the null hypothesis of non-stationarity of the GDP per capita series.

The upper part of table 6 reports the estimation results. The lagged GDP per capita variable, as expected, has a positive and significant estimated coefficient, which in the context of our technology-gap model is interpreted as evidence of a catching up mechanism linked to the international diffusion of advanced technologies. The investment variable is also positive and significant in the estimations, confirming the important role of the process of physical capital accumulation for economic growth.

Innovative activities are measured by means of two variables, the patent indicator and the scientific articles variable (the latter available only for the shorter time span). Both of them turn out to be positively related to the dynamics of income per capita, and their estimated coefficients are significant and quite stable throughout the regressions. This result is in line with the convergence analysis previously presented, which has shown that the dynamics of both innovative activities and GDP per capita is characterized by increasing polarization between rich and poor countries and the gradual catching up (or vanishing) of the middle-income group. Our model interprets this empirical pattern as evidence of the important role played by innovative activities for economic dynamics, and as an indication that one major reason behind the increasing income disparities in the world economy is related to cross-country differences in the intensity of innovative efforts.

The next four variables measure the role of human capital (secondary and higher education) and technological infrastructures (electricity and fixed telephony¹⁸). One of these indicators, the electricity variable, is highly correlated to the other measures of human capital and infrastructures, thus leading to a problem of multicollinearity in the regressions. For this reason, we also report the results of regressions that do not include the electricity variable, and which are therefore able to estimate with greater precision the effect of the other regressors (see columns 1, 3, 4 and 6).

The two variables measuring human capital are positive and significant in most of these experiments. The higher education variable, in particular, appears to have a stronger impact on income per capita in the shorter than in the longer period. Interestingly, while previous analyses frequently failed to identify a positive and significant relationship between human capital and growth (see discussions in Benhabib and Spiegel, 1994, and Pritchett, 2001), our finding suggests that more advanced education levels are indeed correlated with economic growth in the last two-decade period in a panel data setting, and that tertiary education is progressively becoming a more crucial aspect to explain cross-country differences in economic performance.

The two indicators of technological infrastructures, electricity and fixed telephony, are also positive and significant (see columns 2, 3, 5 and 6). This provides support for the hypothesis pointed out by our theoretical model. Technological infrastructures matter for the growth and development process since they may contribute to strengthen the absorptive capacity of a country as well as the productivity of its research activities. In fact, the regressions presented in columns 2, 3, 5 and 6, which add technological infrastructures to human capital, provide evidence for this hypothesis and improve the standard formulation based on human capital alone, which is the base specification tested in columns 1 and 4 (e.g. Benhabib and Spiegel, 1984; Papageorgiou, 2002).

Summing up, the analysis undertaken in this section indicates that the world distribution of GDP per capita is characterized by increasing polarization between rich and poor economies, and that this dynamics is closely related to the following main factors: (1) the process of physical capital accumulation; (2) a catching up mechanism linked to the international diffusion of advanced technologies; (3) technological infrastructures and human capital, which can foster both the ability of a country to imitate foreign technologies and the productivity of its R&D sector; (4) the intensity of innovative activities.

Our analysis of technological convergence in the previous section indicates that, while the third factor (conditions supporting knowledge imitation and creation) is characterized by an overall process of cross-country convergence, the fourth one has experienced divergence and a pattern of increasing polarization between rich and poor countries. Innovative activities represent therefore a crucial dimension that developing economies should more actively upgrade and focus on during the catching up process.

Table 6. Growth accounting regressions – Results of dynamic panel model estimation (Arellano-Bond GMM estimator)

	Longer period: panel 1970-2000			Shorter period: panel 1985-2000		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta GDPPC$	0.7016 (43.72)***	0.5384 (21.71)***	0.5906 (26.34)***	0.5602 (50.97)***	0.4899 (23.98)***	0.5377 (27.87)***
ΔINV	0.1732 (13.05)***	0.1196 (7.52)***	0.1791 (11.33)***	0.1789 (14.38)***	0.1205 (13.69)***	0.1584 (11.00)***
ΔINN (Patents)	0.0434 (13.98)***	0.0473 (13.25)***	0.0591 (25.20)***	0.0437 (23.37)***	0.0248 (6.07)***	0.0432 (18.11)***
ΔINN (Articles)				0.0845 (13.51)***	0.0616 (8.18)***	0.0818 (15.98)***
ΔHK (Secondary)	0.0022 (0.20)	-0.0174 (1.19)	0.0532 (3.30)***	-0.0177 (1.28)	-0.0349 (1.68)*	0.0291 (2.02)**
ΔHK (Higher)	0.0463 (5.89)***	-0.0342 (4.68)***	0.0259 (1.64)*	0.0565 (6.56)***	-0.0609 (5.44)***	0.0383 (5.94)***
ΔTI (Electricity)		0.1988 (9.26)***			0.2229 (28.62)***	
ΔTI (Telephony)		0.0064 (2.04)**	0.0144 (11.23)***		0.0055 (1.19)	0.0079 (5.60)***
Constant	0.0089 (3.57)***	0.0102 (3.42)***	0.0114 (4.95)***	0.0144 (4.65)***	0.0226 (7.67)***	0.0048 (1.57)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sargan test	68.12	55.60	57.59	56.87	55.64	56.09
Autocorrelation (1)	-3.83***	-3.76***	-3.86***	-2.73***	-2.63***	-2.73***
Autocorrelation (2)	0.36	1.34	0.50	-0.08	0.84	-0.15
Wald χ^2	7626.69	3641.37	19749.9	40926.7	27083.1	235256.8
Countries	74	67	68	65	63	64
Observations	428	339	342	184	177	180
Panel unit root tests	LLC (4) -4.41***	LLC (5) -5.37***	IPS (4) -5.24***	IPS (5) -6.30***	FT (4) -2.64***	FT (5) -3.44***

Notes: Arellano and Bond GMM two-step estimator. T-statistics between parentheses.

*** Significance at 1% level; ** Significance at 5% level; * Significance at 10% level.

The panel unit root tests have been carried out on the log GDP per capita series (yearly data) for the countries included in the regressions. All three tests (LLC: Levin-Lin-Chu; IPS: Im-Pesaran-Shin; FT: Fisher type test) include a constant and a time trend in the augmented Dickey Fuller equation. The number of lags have been selected based on the AIC (the numbers between parentheses indicate the maximum number of lags that have been considered for each test).

6. Conclusions

Countries in the world economy are characterized by remarkably different levels of technological development. The paper has shown that there exist, in particular, three distinct technology clubs. The technology gaps that separate these country groups are large with respect to all the main dimensions of technology that have been considered by our theoretical model, namely human capital, technological infrastructures and innovative activities. This fact is relevant because, before implementing policies aimed at developing the knowledge base of a country, it is important to carefully assess its strengths and weaknesses, and its relative position *vis-à-vis* more advanced countries. Since countries can only imitate and adopt technologies that are *appropriate* to their development level (Basu and Weil, 1998), technology policies should also be appropriate and specifically targeted to a set of country-specific possibilities and objectives. Our findings suggest, in particular, that the current emphasis on the need for developing countries to invest and rapidly adopt ICT-related infrastructures should be complemented by an equally great effort to build up and upgrade more traditional infrastructures.

Notwithstanding the existence of large technology gaps, the empirical evidence on the technological dynamics across countries provides some encouraging indications. In the last couple of decades, less developed economies have in fact been able to partly close the large distance separating them from the other two groups in terms of both human capital and technological infrastructures. These two factors are important because they may contribute to strengthen a country's absorptive capacity as well its innovative capability. The convergence pattern experienced by these two dimensions in the last two-decade period is crucial not only for the impacts it has had on the dynamics of income, but also because human skills and technological infrastructures constitute important aspects of welfare. In other words, they are not simply means to achieve economic progress, but do also constitute

achievements that are directly relevant for human development, representing therefore important targets for policy.

The dimension of technology where developing economies have not yet achieved considerable progress, and where they have actually experienced an increase in the technology gap, refers to the intensity of innovative activities. The latter dimension is in fact characterized by a process of increasing disparities between rich and poor economies, which closely resembles the evolution of the world income distribution. Innovative activities represent therefore a crucial dimension that developing economies should more actively upgrade and focus on during the catching up process.

In order to get closer and eventually jump to the innovation development stage, developing economies should implement an appropriate combination of policies that takes into account the need to simultaneously develop R&D activities, traditional infrastructures, ICTs and advanced human skills. Referring to this latter aspect, our analysis has in fact shown that, as developing and middle-income countries get closer to the technological frontier, tertiary education becomes the most crucial aspect of human capital, while primary and secondary education progressively become less relevant factors to explain differences in economic performance across countries.

In sum, the perspective adopted in this paper and the related empirical findings suggest that the interaction among different dimensions of technology constitutes a crucial factor of growth and catching up. Policies aimed at closing the technology gap should therefore undertake an active effort to simultaneously build up and upgrade the various complementary aspects that constitute each country's capability to imitate foreign technologies and its ability to create new advanced knowledge.

Appendix 1: The composition of the technology clubs

Cluster 1: Advanced:

Japan, US, Germany, Netherlands, Switzerland, UK, Denmark, Finland, Iceland, Norway, Sweden, Australia, Canada, New Zealand, Israel.

Cluster 2: Followers:

Honk Kong (↑), South Korea (↑), Singapore (↑), Malaysia, Philippines, Thailand, Fiji, Austria (↑), Belgium (↑), France (↑), Luxembourg, Cyprus, Greece, Ireland, Italy, Malta, Portugal, Spain, Turkey, Bahrain, Jordan, Kuwait, Lebanon, Saudi Arabia, Syria, United Arab Emirates, Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Jamaica, Mexico, Panama, Paraguay, Peru, Puerto Rico, Uruguay, Venezuela, South Africa, Trinidad and Tobago, Armenia, Azerbaijan, Belarus, Bulgaria, Croatia, Czech Republic, Georgia, Estonia, Hungary, Kazakhstan, Kyrgyz Republic, Latvia, Lithuania, Macedonia, Moldova, Poland, Romania, Russian Federation, Slovak Republic, Slovenia, Tajikistan, Turkmenistan, Ukraine, Uzbekistan

Cluster 3: Marginalized:

China (↑), Indonesia (↑), Vietnam (↑), Bangladesh, India, Mongolia, Nepal, Papua New Guinea, Pakistan, Sri Lanka, Iran (↑), Oman (↑), Yemen, Albania (↑), El Salvador (↑), Guyana (↑), Honduras (↑), Guatemala, Haiti, Nicaragua, Algeria (↑), Botswana (↑), Mauritius (↑), Tunisia (↑), Zimbabwe (↑), Benin, Cameroon, Central African Republic, Congo Rep., Cote d'Ivoire, Egypt, Gabon, Ghana, Kenya, Lesotho, Madagascar, Malawi, Morocco, Mozambique, Namibia, Nigeria, Senegal, Sudan, Swaziland, Tanzania, Togo, Uganda, Zambia.

Notes: The arrows indicate those countries shifting towards the upper cluster between the beginning and the end of the period.

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Notes

1. The idea that technology is a major factor to explain cross-country differences in growth performance is also supported by a growing number of empirical works (e.g. Hall and Jones, 1999; Easterly and Levine, 2001). Overviews of the literature on technology and convergence have been presented by Fagerberg (1994), Islam (1999) and Gong and Keller (2003).
2. For instance, in previous decades, the discovery and wide diffusion of GPTs such as telephony and electricity have greatly enhanced the interrelatedness and the connections among firms, as well as their productive efficiency. More recently, innovations based on ICTs (e.g. mobile telephony, Internet) have dramatically increased the network capabilities of economic agents.
3. The multiplicative form employed in equation 3 indicates that HK and TI are assumed to have an interaction effect on absorptive capacity. To illustrate this idea, the availability of advanced human skills may increase the possibility to make a more productive use of advanced technological infrastructures such as the Internet; in turn, Internet and ICT-based networks may enhance the access to data and information, thus benefiting more educated workers.
4. In the special case where $\theta_1 = \delta_1 = 0$, we are back to the standard formulation where it is only human capital that enters the knowledge imitation and creation functions (e.g. Benhabib and Spiegel, 1994).
5. For some of the indicators, data for a large sample of countries are only available for a slightly shorter period. The precise time span for each indicator is indicated as follows. Patents: 1985-2003; Scientific articles: 1986-2001; Internet: 1994-2004; Mobile telephony: 1993-2003; Fixed telephony: 1985-2003; Electricity consumption: 1985-2003; Tertiary enrolment ratio: 1991-2003; Higher schooling: 1980-2000; Secondary enrolment ratio: 1991-2003; Total schooling: 1980-2000; Primary enrolment ratio: 1980-2000; Literacy rate: 1990-2004.
6. In addition to those presented here, R&D would have been another useful indicator of innovative intensity. However, it has not been used here because its country coverage is much more limited than it is the case for the other two innovation variables.
7. For each aspect considered here (tertiary, secondary and basic education), we have chosen to use two different indicators, one referring to the period 1980-2000 (source: Barro and Lee, 2001), and the other to the period 1990-2004 (source: World Bank, 2006). This makes it possible to check the robustness of our empirical results, so to ensure that they do not depend on the time span available for each indicator.
8. Relatedly, one possible disadvantage of using a large number of indicators is that some of them also reflect other aspects of the development process like consumption and investment patterns, as it is for instance the case for our indicators of fixed and mobile telephony, electricity and education levels. This limitation is, however, not easy to overcome, since indicators that try to measure a complex concept such as the one of *absorptive capacity* are inevitably closely related to a country's overall level of development and, hence, to a broad set of other aspects of an economic, institutional and social nature.
9. The cluster analysis has carefully analysed the robustness of these results by experimenting with different input variables and different clustering methods. The exercise has also been repeated at the beginning and the

end of the period to assess the stability of the results over time. The three-cluster pattern that is presented here is robust to these modifications.

10. In other words, the (unconditional) convergence analysis presented in this section does not assume or test any theoretical convergence model. By contrast, in the absence of a theoretical framework suggesting how these three technological dimensions precisely evolve, our empirical analysis simply aims at *measuring* the direction and rate of change of their dynamics, without relating them to any other possible explanatory factor.

11. The notion of σ -convergence has increasingly been used in applied growth theory in recent years, and it has constituted the basis for developing new methods for analysing the evolution of the world distribution of income over time (Quah, 1996a, 1996b, 1996c).

12. Note that this result is not affected by the fact that a few fast catching up economies (e.g. China, Asian NICs) have passed from the lower to the upper cluster over time. In the analysis of cluster convergence, in fact, these few dynamic shifting-cluster economies (listed in Appendix 1) have not been considered as part of the upper cluster. If they had been included in the latter, they would have decreased the centre of the lower cluster and, hence, they would have biased the evidence in favour of divergence between the two clubs. In other words, the analysis of cluster convergence requires that the cluster composition must be held constant over the investigation period.

13. This result is consistent with the recent empirical study of Feyrer (2008), which has identified a close relationship between the evolution of the world income distribution and the dynamics of TFP.

14. For a related growth accounting exercise in a standard cross-country OLS framework, see Benhabib and Spiegel (1994). For more general presentations and discussions of the growth accounting methodology, see Easterly and Levine (2001) and Caselli (2005).

15. Note that since the β coefficient is usually expected to be negative (in the presence of cross-country convergence), when the growth equation is specified as in equation (14) the estimated coefficient is instead expected to be positive (and smaller than 1, in the presence of convergence). This expectation is also in line with the stationarity condition (see the panel unit root tests reported in the bottom part of table 6).

16. Recall in fact the parameter definitions previously set out in section 2: $a = (\theta_1 + \delta_1)$; $b = (\theta_2 + \delta_2)$.

17. It should be noticed that, while the advantage of the panel dataset is to exploit the time series variation in the cross-country dataset, the common disadvantage is that most of the variables are only available in panel form for a somewhat more limited sample of countries. The panel regression results presented here do in fact refer to a sample of around 70 economies, which is smaller than the whole cross-country sample that was used in the previous sections.

18. The indicators of ICT infrastructures considered in previous sections, mobile telephony and Internet, are available only for a shorter time span and cannot be used in a panel setting as the other variables. We have therefore not been able to consider these ICT-related variables in the panel estimations.