DRUID Working Paper No. 06-21

Convergence and Divergence among Technology Clubs

By

Fulvio Castellacci

Danish Research Unit for Industrial Dynamics

www.druid.dk

Convergence and Divergence among Technology Clubs

Fulvio Castellacci
Department of International Economics
Norwegian Institute of International Affairs (NUPI)
POB 8159, Dep. 0033 Oslo, Norway
E-mail: fc@nupi.no

Abstract:
The paper investigates cross-country differences in technology in a large sample of developed and developing economies over the 1990s. The empirical analysis indicates the existence of three technology clubs with markedly different levels of technological development: advanced, followers and marginalized countries. The technology clubs also differ with respect to their dynamics over the 1990s. While the club of followers is characterized by a process of gradual convergence towards the technological frontier, the group of marginalized has experienced an increase in its gap in terms of innovative capabilities.

Key words: Growth and development; technological change; convergence clubs; polarization

JEL Codes: O11; O33; O40

ISBN 87-7873-212-3

Note:
The paper was presented at the DRUID Conference on "Knowledge, Innovation and Competitiveness: Dynamics of Firms, Networks, Regions and Institutions", Copenhagen, June 2006. I wish to thank Daniele Archibugi, Myriam Cloodt, Tim Kastelle, Bart Los, Alessandro Nuvolari and Alessandro Sterlacchini for their very helpful comments and suggestions. The usual disclaimers apply.

1. Introduction

Applied growth theory has experienced significant advances in the last ten years. Moving away from the traditional cross-country growth regression framework, empirical works have made use of a wide array of different econometric techniques, and have pointed out the great heterogeneity of countries' characteristics and growth behaviour. The study of the variety of macroeconomic growth patterns now constitutes a central research theme in growth theory (Temple, 1999).

Already two decades ago, Baumol (1986) observed the existence of three *convergence clubs* in the world economy, i.e. three groups of countries that, due to their differences in terms of initial conditions, tend to follow diverging growth trajectories over time. Baumol's original insight has inspired a great amount of applied research in the last few years. Durlauf and Johnson (1995) developed this idea further, and classified world countries into four groups according to their variety in initial conditions (i.e. initial levels of GDP per capita and of literacy rate). Their empirical study confirmed the existence of different convergence clubs with markedly different characteristics and growth behaviour, and inspired a set of subsequent empirical works (Desdoigts, 1999; Hobijn and Franses, 2000; Johnson and Takeyama, 2001; Fiaschi and Lavezzi, 2003; Canova, 2004; Paap et al., 2005).

The idea that countries that differ in terms of initial conditions experience diverging growth performances has also inspired a set of related contributions, which have studied the evolution of the world distribution of income 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 in the last decade (e.g. Bianchi, 1997; Jones, 1997; Paap and van Dijk, 1998; Anderson, 2004).

What are the factors that may explain these empirical findings on clustering, polarization and convergence clubs? One common answer, pointed out by multiple equilibria models (e.g. Azariadis and Drazen, 1990), is related to threshold externalities in the accumulation of physical and human capital. One major alternative explanation, recently proposed by Schumpeterian endogenous growth models (Howitt, 2000; Howitt and Mayer-Foulkes, 2005), points to innovation and to the international diffusion of new technologies as the possible sources of polarization and convergence clubs.

Economic historians (Gerschenkron, 1962; Landes, 1969) have long ago argued that developing countries may exploit their backwardness position by imitating and adopting new technologies produced in advanced economies, but they have also shown that the process of imitation is costly, and it requires the existence of technological capabilities that many developing countries lack (Abramovitz, 1986). In this framework, the basic reason for the existence of different clubs in the world economy is that countries greatly differ in terms of their technological capabilities, and, hence, in terms of their ability to catch up by imitating foreign technologies. Countries with greater levels of technological development are able to catch up and to converge gradually towards the club of advanced economies, while countries with lower capabilities are not able to exploit the scope for catching up, and inexorably fall further behind.[1]

This general hypothesis leads to one major question. Does the empirical evidence support the idea of the existence of clubs of countries characterized by different levels of technological development and different technological dynamics? This question has not been considered yet in applied growth theory. It constitutes an important research question for the literature on clustering, polarization and convergence clubs, and this paper aims at investigating it.

The purpose of the paper is thus to study the existence, characteristics and dynamics of different *technology clubs* in the world economy. The paper, empirical in nature, will explore the existence of groups of countries characterized by different levels of technological development, point out their characteristics and the technological distance that separates them, and analyse their different dynamics over time.

The analysis makes use of the ArCo database, a dataset recently constructed by Archibugi and Coco (2004a; 2004b) that contains a set of indicators on various aspects of countries' technological activities for a large number of developed and developing economies. The sample is constituted by 131 countries, whose technological levels are measured at two different points in time, at the beginning and at the end of the 1990s. The dataset makes it possible to consider various aspects of

[1] The idea that technology is a major factor to explain cross-country differences in growth performance is not only interesting from a theoretical point of view, but it is also supported by a large number of empirical works (e.g. Bernard and Jones, 1996; Prescott, 1998; 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). For a more general discussion of the study of technological change and economic growth in different strands of research, see Castellacci (2006).

countries' technological capabilities, such as their ability to create and to imitate new technologies, their technological infrastructures and their education levels.

The paper is organized as follows. Section 2 presents the data and the indicators used to measure countries' technological capabilities. Section 3 reports the results of a hierarchical cluster analysis, which 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.

Section 4 shifts the focus to the study of the dynamics of these technology clubs. The analysis of cross-country patterns of technological change makes use of four different notions of convergence. Two of them are the well-known concepts of β-convergence and σ-convergence. The other two are new notions of convergence that the paper puts 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 distributions of the growth rate of the technology indicators, while the second (cluster convergence) is based on the dynamics of the technology-gaps over time.

The results of the convergence analysis show that the technology clubs are characterized by very different dynamics of technological change over the 1990s. While the club of followers is characterized by a process of gradual convergence towards the technological frontier, the group of marginalized has experienced an increase in its gap in terms of innovative capabilities. Section 5 concludes the paper by summing up the results and by pointing out their contribution to the applied growth literature.

2. Data and indicators of technological capabilities

Technological change is a complex and multifaceted aspect of economic progress. Countries' technological capabilities are strictly related to a number of different aspects, such as the basic and advanced human capital base, the infrastructures that support industrial production and innovative activities, and the country's ability to create, imitate and manage a complex pool of advanced technological knowledge.

The complexity of the concept of technology presents a formidable challenge to its measurement in empirical analyses. In the literature on technology and convergence, the standard approach to measure technological change is to rely on an *indirect* measure, the so-called 'productivity residual' or 'total factor productivity' (TFP; see Prescott, 1998; Islam, 1999; Easterly and Levine, 2001). In an attempt to provide a richer characterization and a more precise measurement of countries' levels of technology, this paper follows a different strategy, and makes use of a set of indicators that measure *directly* various relevant aspects of countries' technological capabilities.

The empirical analysis is based on the ArCo database, a dataset recently constructed by Archibugi and Coco (2004a; 2004b) that includes a set of indicators of technology and technological capabilities for a large number of developed and developing economies. The sample used in this paper is constituted by 131 countries (listed in Appendix 2), whose technological capabilities are measured at two different points in time, at the beginning and at the end of the 1990s. The indicators are briefly described as follows.[2]

Patents: Number of patents registered at the US Patent and Trademark Office per million people (USPTO, 2002). This is a measure of the technological innovations generated for commercial purposes. Patents represent a form of codified knowledge generated by profit-seeking firms and organisations.[3]

Scientific articles: Number of scientific articles per million people (NSF, 2000 and 2002).[4] Scientific literature is another important source of codified knowledge. It

---

[2] For a more complete description of the dataset and the methodology used to construct it, see Archibugi and Coco (2004a), while the main differences between the ArCo technology index and other similar analyses to measure countries' technological capabilities are described in Archibugi and Coco (2004b).

[3] To account for yearly fluctuations (which might affect the results in small and medium sized countries), we have considered a four-year moving average for the 1987-1990 and 1997-2000 periods. Patents are a good proxy of commercially exploitable and proprietary technological inventions, but we are well aware that many inventions are not patented, especially among those invented in developing countries. For surveys on patents as internationally comparable indicators, see Pavitt (1988) and Archibugi (1992).

[4] The source of these data is the Science Citation Index generated by the Institute for Scientific Information, which is the most comprehensive and validated available source on scientific publication. It reports information on the scientific and technical articles published in a sample of about 8,000 journals selected among the most prestigious in the world. The fields covered are: physics, biology, chemistry, mathematics, clinical medicine, biomedical research, engineering and technology, and earth and space sciences. Article counts are based on fractional assignments; for example, an article with two authors from different countries is counted as one-half article to each country.

represents the knowledge generated in the public sector, and most notably in Universities and other public research centres, although researchers working in the business sector publish a significant and growing share of scientific articles.

Internet penetration: Number of Internet users per 1,000 people (ITU, 2001; World Bank, 2003).[5] Internet is a new technology that has quickly become the keystone of the Information and Communication Technology, but it was not commercially available yet in 1990. For this reason, we have postponed the beginning of the period to 1994.

Telephone penetration: Sum of telephone mainlines and mobile phones, per 1,000 people (ITU, 2001; UNDP, 2001; World Bank, 2003).[6] Telephony, both in fixed and mobile forms, constitutes a fundamental infrastructure for business purposes, and it allows tracing populations with human skills and acquiring technical informations.

Electricity consumption: Number of kilowatt of electricity consumed per hour per capita. This measures the production of power plants and combined heat and power plants, less distribution losses, and own use by heat and power plants (see World Bank, 2003, table 5.10). This indicator accounts for the oldest technological infrastructure. Electricity consumption is also a proxy measure for the use of machinery and equipment since most of it is generated by electric power.[7]

Tertiary science and engineering enrolment: Share of tertiary students in science and engineering in the population of that age group (UNESCO, 2002; World Bank, 2003). This variable is a measure of the formation of advanced human capital in science and

---

[5] Internet users access a worldwide network. They differ from Internet hosts, which are computers with active Internet Protocol (IP) addresses connected to the Internet. The data on users, when available, are preferable to those on hosts for two reasons: first, they give a more precise idea of the diffusion of Internet among the population; second, some hosts do not have a country code identification and in statistics are assumed to be located in the United States, thus causing a bias towards this country.

[6] We have chosen to assign equal weights to fixed and mobile phones because, although they incorporate different degrees of technology, they share the same function.

[7] Other valuable measures of industrial capacity developed, for example, by Lall and his colleagues (see Lall and Albaladejo, 2001; UNIDO, 2002) are available for a smaller number of countries only.

technology, which represents a necessary requirement for acquiring and managing advanced technological knowledge.

Mean years of schooling: Average number of years of school completed in the population over 14 (Barro and Lee, 2001; UNDP, 2001; World Bank, 2003). Although this indicator does not consider differences in the quality of schooling across countries, it constitutes a widely used proxy of the level of basic human skill.

Literacy rate: The percentage of people over 14 who can, with understanding, read and write a short, simple statement on their everyday life (UNDP, 2001; World Bank, 2003). The literacy rate is a necessary precondition for the development of human skills and of basic and advanced human capital.

These eight indicators are those that we will use to analyse cross-country differences in technological capabilities in the 1990s. The advantage of using a large number of indicators is that we are able to provide a more precise characterization of countries' technological level than if we were using one single indirect measure such as the TFP. This is particularly important in a large sample that includes countries characterized by very different levels of technological and economic development.

However, a major difficulty in using these indicators is that they represent to a great extent strictly related (and not easily separable) aspects of countries' technological capabilities. Variables measuring the creation and diffusion of new technologies, technological infrastructures and human skills tend in fact to be highly correlated, as they all constitute complementary dimensions of national technological capabilities. Thus, before proceeding to the core of our empirical analysis, the study of cross-country differences in technology, it is important to reduce this large set of indicators to a smaller number of *distinct* (not overlapping) dimensions.

A factor analysis has been performed in order to select the best explanatory variables used to identify cross-country differences in technological capabilities, i.e. those variables that better discriminate between countries' technological level.[8] The

[8] Interestingly, in a comprehensive survey of growth theory, Temple (1999, p. 148) argues: "Despite some interest from development economists, simple techniques for data reduction like factor analysis and principal components have been largely ignored by recent growth researchers. Their use seems to have a great deal of potential". For previous papers applying factor analysis to the study of economic growth and development, see Adelman and Morris (1965) and Temple and Johnson (1998).

purpose of the factor analysis is to extract a smaller number of factors that are able to account for most of the variance in the sample.[9]

Table 1 presents the results of the factor analysis for our ArCo dataset for the years 1990 and 2000. In both years, the principal component analysis identifies two major factors, which, taken together, explain a large percentage of the variability in the sample (between 78 and 82%).[10] Our interpretation of the factor solutions is the following.

Factor 1 may be interpreted as a broad measure of *technological infrastructures and human skills*. This principal component loads in fact very high on all the variables measuring technological infrastructures (telephone penetration and electricity consumption) and those measuring education levels and human skills (tertiary science and engineering enrolment, mean years of schooling, and literacy rate). The extraction of this first factor shows that these two aspects of technological capabilities, infrastructures and human skills, are highly correlated and strongly complementary to each other. Both of them contribute to define each country's ability to imitate and to implement foreign advanced technologies (Abramovitz, 1986), which is a key requirement for developing economies that try to reduce the huge gap that separates them from the technological frontier. Factor 1, a linear combination of these five variables, accounts for around 45% of the variance in the sample in both periods, and it therefore appears as a very relevant dimension to investigate cross-country differences in technological capabilities in the 1990s.

Factor 2 may be interpreted as a measure of *the creation and diffusion of codified knowledge*. It is highly correlated with variables measuring the creation of codified technological knowledge by private firms and the public sector (i.e. patents per capita and the production of scientific articles), and its diffusion (measured by the Internet penetration). The factor indicates that the creation and diffusion of advanced

---

[9] The eight indicators of countries' technological capabilities have been standardized before entering the factor analysis. The general formula used to standardize the indicators adopts the "distance from the best and the worst performers" method of standardization, which is the same used for the indicators composing the Technology Achievement Index (UNDP, 2001; Desai et al., 2002) and the ArCo Technology Index (Archibugi and Coco, 2004a and 2004b). Different methods of standardization could have been used, but the choice of a different standardization method would have not affected the results of the factor analysis.

[10] The graphical inspection of the so-called Scree diagram (available on request) indicates that the extraction of additional factors after the second contributes only marginally to the overall percentage of variance explained. The two-factor solution may thus be regarded as the most efficient, in the sense that it explains a large portion of the variability in the sample by using only a small number of factors.

technologies are to a large extent related and complementary aspects of countries' technological activities (Cohen and Levinthal, 1989). Both contribute to determine the innovative capability, which is a fundamental requirement to compete in the modern knowledge-based economy, particularly for countries that are already close to the technological frontier. Factor 2 is a linear combination of these three variables, and it accounts for about one third of the variance in the sample. Thus, together with factor 1, it appears to be a very important aspect to study differences in technological capabilities in the world economy.

Figure 1 reports the kernel density estimates of the statistical distributions of these two principal components in 1990 and 2000. The graphs show clearly that the shapes of the distributions of the two factors are very different. The thick and long left tail of factor 1 suggests the existence of a great cross-country variability of technological infrastructures and human skills within the large group of less developed economies. On the contrary, factor 2 shows a long right tail, which indicates that innovative capabilities are very low for most developing countries in the sample, while they vary significantly within the group of middle income and advanced countries. Given that the purpose of this paper is to analyse differences in technological capabilities in a very large sample of 131 countries, including both developing and developed economies, both factors identified by the principal component analysis will be used in the subsequent empirical analysis.

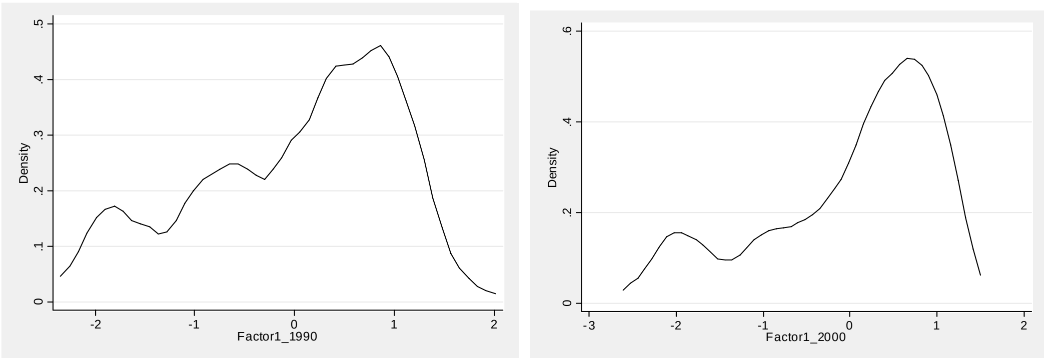
Table 1: Results of the factor analysis, year 1990 and 2000*

	1990		**2000**	
	Factor 1: Technological infrastructures and human skills	**Factor 2: Creation and diffusion of codified knowledge**	**Factor 1: Technological infrastructures and human skills**	**Factor 2: Creation and diffusion of codified knowledge**
Patents per capita	0,18	**0,86**	0,17	**0,89**
Scientific articles	0,35	**0,86**	0,34	**0,89**
Internet penetration	0,28	**0,78**	0,38	**0,81**
Telephone penetration	**0,86**	0,34	**0,86**	0,34
Electricity consumption	**0,85**	0,29	**0,84**	0,34
Tertiary S&E enrolment	**0,74**	0,29	**0,65**	0,51
Mean years of schooling	**0,80**	0,42	**0,79**	0,45
Literacy rate	**0,91**	0,12	**0,91**	0,10
% of variance explained	46,27	32,00	45,12	37,21
Cumulative % of variance explained	46,27	78,28	45,12	82,33

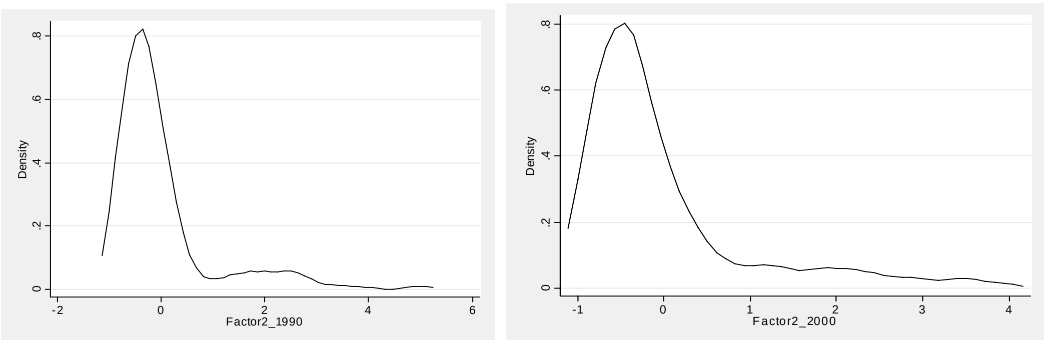
* Extraction method: Principal components.
Rotation method: Varimax with Kaiser normalization.

Figure 1: Kernel density estimates of the two principal components *

Factor 1, in 1990 (left) and 2000 (right)



Factor 2, in 1990 (left) and 2000 (right)



* Epanechnikov kernel function.
Halfwidth of kernel: Factor 1: 0,20; Factor 2: 0,25.

3. Technology clubs and technology gaps

We will now use these two principal components to investigate the existence and the characteristics of different technology clubs in the world economy in the 1990s. This section presents the results of a cluster analysis that divides the world economy into a few country groups characterized by different levels of technological development.[11] Two different specifications of the cluster analysis have been tested. In the first, the two principal components extracted by the factor analysis in the previous section have been used as inputs in the clustering algorithm. In the second, two variables have been

[11] Recent empirical works using cluster analysis to identify different clubs of countries have been presented by Desdoigts (1999), Hobijn and Franses (2000), Canova (2004) and Paap et al. (2005).

used instead: the literacy rate (corresponding to factor 1) and the number of scientific articles per capita (corresponding to factor 2). These two variables have been selected because (i) they are the ones more strongly correlated to each component of the factor analysis (see table 1), and because (ii) they are the ones whose distribution shapes are more similar to those of the two components. In other words, this means that these two variables are those that best represent (and most closely correspond to) the factors extracted in the factor analysis.[12]

As it is well known, the results of cluster analysis may change substantially when different methods are applied to the same dataset. In order to overcome this problem, we have run around thirty different clustering algorithms. For each of the two specifications, we have proceeded in three steps. First, three distinct *hierarchical agglomerative* methods have been applied (between groups linkage, within groups linkage, Ward's method), and three different ways to measure the distance between cases have been used (Euclidean, squared Euclidean, and cosine distance). Secondly, after having identified the main resulting clusters, an *iterative partitioning* method (K-means procedure) has been applied to check the robustness of the results of the hierarchical agglomerative analysis. Additionally, each clustering algorithm has been run by using as inputs the factors (and the corresponding variables) in both 1990 and in 2000, so to assess the stability of the resulting clusters over time.

The methodology that we have employed has three advantages: (i) it makes it possible to check the robustness of the results to changes in the variables used as inputs, in the clustering method, and in the distance measurement adopted; (ii) it allows investigating whether the resulting clusters are stable over time between 1990 and 2000, both in terms of cluster characteristics and cluster membership; (iii) the hierarchical agglomerative method employed is able to identify *endogenously* the number of clusters that forms the best partition of the dataset (see Appendix 1).

All of the clustering algorithms have produced *three* main clusters, and this result appears to be robust to modifications in the method applied, in the definition of distance measurement adopted, and in the variables used as inputs in the analysis. The existence of three different groups of countries is also apparent from a graphical inspection of the kernel density estimates of the two principal components, which

[12] Both variables have been standardized before entering the clustering algorithms, as it is customary in cluster analysis.

indicate that both of them, and particularly factor 1, are characterized by a three peaks distribution (see Figure 1, section 2).

The three resulting clusters are to a large extent the same in 1990 and 2000, with only a few changes of cluster memberships between the two periods, thus showing a remarkable stability of the resulting clusters during the decade. The major characteristics of these three technology clubs are presented in table 2, the technological distance between them is shown in table 3, and the cluster membership is reported in Appendix 2. The three groups can be described as follows.

Cluster 1: *Advanced.* This is the group of more technologically advanced countries, composed by a small set of industrialized economies (between 15 and 21 countries, less than 15% of the sample's population) that hold approximately 40% of the world GDP. It comprises the traditional leaders, US and Japan, Continental and Northern European economies, and Western offshoots (Australia, Canada, Israel and New Zealand). The cluster membership is quite stable over time, the main difference being the entry of a few very dynamic Asian NICs (Hong Kong, South Korea and Singapore) into this restricted technology club in 2000.

Table 2 shows that at the beginning of the period the group is characterized by high levels of creation and diffusion of codified knowledge (on average, around 69 patents, 627 scientific articles and 27 Internet users per capita), well-developed technological infrastructures (in terms of both telephones and electricity consumption), and high levels of basic and advanced education (nearly 11% tertiary enrolment ratio in science and engineering, 10 mean years of schooling, and 99% literacy rate).

The cluster does also prove to be very dynamic over time, with rapid growth rates of technological capabilities between 1990 and 2000, particularly in terms of patents (+40%), Internet users (+986%), telephones (+104%) and tertiary enrolment ratios in science and engineering (nearly +60%). Thus, the technological frontier has advanced rapidly in the last decade, making the catching-up process of follower countries more and more demanding.

Cluster 2: *Followers.* This is a larger group, composed by around 70 countries (around 27% of the sample's population in 1990) that accounted for 36% of the world GDP at the beginning of the period. The cluster membership is quite stable between 1990 and 2000, and its core is constituted by catching-up economies from South-East

Asia, the South of Europe, the Middle East, Latin America, plus the large group of Former Socialist countries.

There are only a few notable changes to this general pattern over time. In 2000, the main exit is constituted by a small set of dynamic Asian and Continental European economies that abandon the group and move towards the 'advanced' technology club, while the entry is that of a small number of fast catching-up developing countries, from Asia, the Middle East, Central America and Africa, which have rapidly improved their technological capabilities in the 1990s.

Compared to the advanced cluster, this group shows a much lower ability to create and to imitate advanced knowledge, as measured by the number of patents, scientific articles and Internet users. In fact, table 3 indicates that at the beginning of the 1990s the innovation-gap between the 'advanced and the 'followers' group is very huge (around 16:1 for patents, 9:1 for articles and 11:1 for Internet users). Over the decade, the technological distance has gradually decreased in terms of patents and articles, and much more rapidly in terms of Internet users. However, the innovation-gap *vis-à-vis* the economies in the advanced cluster does remain considerable at the end of the decade. On the other hand, the technological distance between this second group and the more advanced one is significantly lower in terms of infrastructures (around 3:1 for telephones and electricity), and education levels (between 1,5 and 2:1), in both 1990 and 2000.

Cluster 3: *Marginalized.* This is the largest group of countries, accounting for more than 60% of the sample's population in 1990, but producing only around 23% of the world GDP at the beginning of the decade. The core of this cluster is constituted by large Asian economies plus nearly all of African countries. The group membership is rather stable in the 1990s, although a restricted number of dynamic economies have managed to catch up and to join the more advanced 'followers' cluster in 2000 (e.g. China, Indonesia, Vietnam, Iran, Oman, and a very few countries from Central America and Africa).

In terms of the ability to create and to imitate new technologies, this group is not only remarkably far from the technological frontier, but also quite distant from the follower countries in the second cluster. Table 3 shows in fact that at the beginning of the period the technological distance between the 'followers' and the 'marginalized' groups is around 190:1 in terms of patents, 14:1 for scientific articles, and 270:1 for

Internet users. During the decade, the gap has diminished very rapidly in terms of Internet users, but it has significantly widened for patents and articles.
Regarding the indicators of technological infrastructures and human skills, the distance *vis-à-vis* the 'followers' cluster at the beginning of the period is equally striking, particularly in terms of telephones (12,2:1), electricity consumption (9,7:1) and tertiary enrolment ratio in science and engineering (5,2:1). Over the 1990s, the gap in terms of technological infrastructures and human skills has decreased slowly, but it still remains huge at the end of the decade.

In short, the results of the cluster analysis lead to the identification of three technology clubs with markedly different levels of technological development. The characteristics of these technology clubs closely resemble those of the 'innovation', 'imitation' and 'stagnation' groups identified by Howitt and Mayer-Foulkes' (2005) recent model. Our findings indicate the existence of two large technology-gaps in the world economy: the first refers to the great distance that separates the group of 'followers' from the technological frontier, particularly in terms of innovative capabilities; the second refers to the impressive gap that separates the 'marginalized' from the 'followers' clubs, both in terms of innovative capabilities and of infrastructures and human capital.

Table 2: Main characteristics of the three technology clubs*

	Cluster 1: Advanced		**Cluster 2: Followers**		**Cluster 3: Marginalized**	
	1990	**2000**	**1990**	**2000**	**1990**	**2000**
Patents granted in USPTO**	69,45	97,37	4,29	6,81	0,02	0,03
Scientific articles**	627,36	670,65	68,56	90,54	4,94	5,63
Internet users (1994 & 2000)***	26,67	289,77	2,48	57,32	0,01	3,51
Fixed and mobile telephones***	516,78	1055,92	163,07	404,72	13,36	47,14
Electricity consumption (kilowatt per hour per capita)	9411,5	10450,9	2584,1	2989,4	265,8	318,5
Tertiary S&E enrolment ratio	10,87	17,31	6,68	9,33	1,28	2,06
Mean years of schooling****	9,91	10,44	6,56	7,06	3,42	3,93
Literacy rate****	98,66	98,80	91,29	93,86	58,01	67,57

* The list of countries included in each cluster is reported in Appendix 2.
** Per million people
*** Per thousand people
**** Population over 14

Table 3: The technological distance between the three clubs*

	Advanced vs. Followers		Followers vs. Marginalized	
	1990	**2000**	**1990**	**2000**
Patents	16,18	14,29	190,3	237,4
Scientific articles	9,15	7,40	13,87	16,09
Internet users (1994 & 2000)	10,77	5,05	270,6	16,32
Fixed and mobile telephones	3,17	2,61	12,20	8,58
Electricity consumption	3,64	3,50	9,72	9,39
Tertiary S&E enrolment ratio	1,63	1,85	5,21	4,54
Mean years of schooling	1,51	1,48	1,92	1,79
Literacy rate	1,08	1,05	1,57	1,39

* The first and second columns report the ratio between technological capabilities in the 'advanced' and 'followers' clusters, in 1990 and 2000. The third and fourth columns report the ratio between technological capabilities in the 'followers' and 'marginalized' clusters in 1990 and 2000.

4. Technological convergence and divergence over the 1990s

The existence of different technology clubs in the world economy is not only interesting *per se*, but it is also relevant because it may contribute to shed new light on the issue of convergence and divergence, which has increasingly attracted the attention of growth theorists in the last couple of decades. This section shifts therefore the focus to the dynamics of convergence and divergence in technology over the 1990s.

Our analysis of convergence differs from most previous contributions in applied growth theory in two main respects. First, we focus on the dynamics of technology, rather than that of income or GDP per capita. This is important, because technological change is a major engine of economic growth, so that the identification of empirical patterns in terms of technological convergence and divergence may have important implications for understanding the current and future evolution of the world income distribution. Secondly, given that data on technological capability for a large sample of countries are only available for a relatively short period of time, we focus on convergence and divergence over the 1990s. This time span is relatively short, but it refers to a particularly interesting and significant period of the world economy, given that the 1990s mark the emergence and rapid diffusion of the new ICT-based general-purpose technologies. In this context, the analysis of technological convergence and divergence is of paramount importance for studying whether the diffusion of the new technologies is leading to decreasing or increasing polarization between rich and poor countries.

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 will 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 capabilities.

4.1 β-convergence

The notion of β-convergence is the most widely used in growth theory, and it has been studied by a huge amount of empirical works (for overviews, see Temple, 1999, and Islam, 2003). The standard approach in so-called cross-country growth regressions is to study the relationships between the growth of GDP per capita and a set of explanatory variables, the most important of which is the level of income at the beginning of the period. If the estimated coefficient of the latter turns out to be negative in the estimations, this is taken as evidence of (conditional) β-convergence, meaning that, on average, poor countries grow more rapidly than rich ones.

In line with this standard approach in growth theory, we investigate here the hypothesis of β-*convergence in technology,* that is the possibility that countries with lower levels of technological development experience a more dynamic technological performance than countries with higher levels (Gerschenkron, 1962; Abramovitz, 1986). In this study of technological convergence, the dependent variable is hence the growth of technology over the 1990s, where technology is calculated by using the ArCo indicators presented in section 2. Given that there exists no previous theory or model suggesting other conditioning variables to include in these technology regressions, the level of technology at the beginning of the 1990s is the only explanatory variable that we include. This means that we refer here to a simple definition of *unconditional* β-convergence in technology, which is studied by running the following cross-country regression:

$$g_i = \alpha + \beta\, y_{i,0} + \varepsilon_i \qquad (1)$$

where g_i is the average growth of the technology indicator i over the period, and y_i is the log of the technology indicator i at the beginning of the 1990s (where i = 1 to 8). The first column of table 4 reports the estimated β coefficients, which turn out to be negative in all the regressions.[13] All indicators suggest therefore the existence of β-convergence in technology, where the speed of convergence is more rapid for Internet and the literacy rate variables (6,6% and 2,5% respectively), and much slower for all other indicators (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 issue also from a different perspective.

4.2 Q-convergence

We propose here a refinement of the notion of β-convergence that may be defined as *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, thus giving an idea of the behaviour of the average of the distribution, a quantile regression estimates a conditional quantile (percentile)

[13] Other details of the regression results, such as the overall significance and the t-statistic for each estimated coefficient, have not been reported to save some space, and are available on request.

function, and therefore makes it possible to analyse the behaviour of different parts of the distribution, including the tails (Koenker and Bassett, 1978; Koenker and Hallock, 2001).

The application of this non-parametric method of estimation to the study of convergence leads us to propose the novel concept of Q-convergence. The latter is thus investigated by running a set of j quantile regressions of the form:

$$g_{i,j} = \alpha + \beta\, y_{i,j,0} + \varepsilon_{i,j} \tag{2}$$

where j is the j_{th} quantile of g_i (i.e. the j_{th} percentile of the growth distribution of the technology indicator i). In other words, we estimate a set of j cross-country regressions, each of which analyses the hypothesis of unconditional β-convergence in technology at a different quantile of the distribution. Q-convergence may therefore be investigated by looking at the vector [β_j], where the j different components of the vector are the coefficients β_j estimated from the quantile regressions (2). By looking at different percentiles of the growth distribution, Q-convergence thus provides a more complete characterization of the dynamics of technological convergence than the simpler notion of β-convergence is able to do.

The results for our ArCo technology indicators are presented in the right-hand side of table 4, where, for each indicator, we report the estimated vector [β_j] corresponding to the 20^{th}, 40^{th}, 60^{th} and 80^{th} quantiles of its growth distribution.[14] 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 patents, scientific articles and telephony, the estimated β coefficient turns out to have a positive sign in correspondence to the lower part of the distribution.

The interpretation of this finding is straightforward. When we focus on the upper quantiles of the growth distribution, i.e. those corresponding to the most dynamic countries in the sample (e.g. China, Asian NICs, etc.), we observe a rapid process of technological convergence, meaning that a few developing economies have been able to grow more rapidly than the other fast growing countries in the sample (which are

[14] Similarly to the OLS regressions previously discussed, other details of the quantile regression results, such as the pseudo R-squared and the t-statistic for each estimated coefficient, have not been reported to save some space, and are available on request.

mostly rich economies already close to the technological frontier). However, technological convergence is by no means a characterizing feature of the whole sample. In fact, when we focus on the lower quantiles of the distribution, poor countries have in most cases not been able to develop their technological capabilities more rapidly than industrialized economies. This is particularly evident for the indicators of patents, scientific articles and telephony, where we indeed observe technological divergence.

In short, the notion of Q-convergence makes it possible to refine the generic (and to some extent misleading) picture presented by the concept of β-convergence, and points out that different parts of the distribution are characterized by very different dynamics and speed of technological convergence. In our study, β-convergence constitutes a useful approximation of the growth behaviour of a few dynamic catching up countries, but it does not provide a precise characterization of the dynamics of several other low performing countries. This point is very relevant for our analysis of technology clubs, and the next two definitions of convergence will investigate it further.

Table 4: β-convergence and Q-convergence in the 1990s*

	β-convergence	**Q-convergence** 20th quantile	40th quantile	60th quantile	80th quantile
Patents	-0,2%	+0,15%	-0,15%	-0,22%	-0,70%
Scientific articles	-0,1%	+0,94%	+0,30%	-0,46%	-0,78%
Internet users (1994 & 2000)	-6,6%	-4,8%	-6,1%	-6,6%	-8,0%
Fixed and mobile telephones	-0,7%	+0,34%	-0,17%	-0,8%	-1,5%
Electricity consumption	-0,4%	-0,27%	-0,19%	-0,28%	-0,32%
Tertiary S&E enrolment ratio	-0,8%	-0,31%	-0,46%	-0,74%	-1,38%
Mean years of schooling	-0,6%	0%	-0,74%	-0,89%	-1,17%
Literacy rate	-2,5%	-2,20%	-2,44%	-2,77%	-3,22%

* The first column reports the β-convergence coefficient estimated from OLS regressions (1). The other four columns report the coefficients of convergence β_j estimated from quantile regressions (2), where j is the j_{th} percentile of the distribution of the growth rate of each technology indicator.

4.3 σ-convergence

While the β-convergence hypothesis focuses on the central tendency of the distribution and investigates the catching up process of poor vs. rich countries, σ-convergence studies whether the dispersion of a target variable has increased or decreased over time, and it thus provides a synthetic measure of the dynamics of the variability of its distribution. 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).

Table 5 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 in 1990 and 2000, and the third column presents their rate of change over the 1990s, which represents a synthetic measure of σ-convergence. The table indicates that all of the technology variables are characterised by a decreasing dispersion over time, and that the speed of σ-convergence is particularly rapid for the indicators of Internet, telephony and the literacy rate (between 20 and 30%), and very low for the variable measuring the tertiary enrolment ratio (less than 2%).

These results give basic support to the findings related to the β- and Q-convergence analysis presented above, which suggest that, in general terms, the evolution of the world distribution of technological capabilities over the 1990s is characterized by an overall pattern of convergence, though different groups of countries seem to have experienced very different dynamics of technological change. This leads to the last part of our convergence analysis, which looks more specifically at the behaviour and relative dynamics of different groups of countries in the world economy.

4.4 Cluster convergence

This is a new notion of convergence, which may be considered as a refinement of the concept of σ-convergence. It develops naturally from the cluster analysis presented in section 3, which has pointed out the existence of three technology clubs with markedly different levels of technological development. 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.[15] 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 1990s.

This notion refines the one of σ-convergence because it makes it possible to investigate whether the observed decrease in the dispersion of the technology

[15] A similar concept of convergence has been recently put forward by Giles (2005) and Giles and Feng (2005).

indicators over the 1990s 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 in the right-hand side of table 5. The table shows that the club of followers has on average decreased its technological distance from the advanced group for nearly all the indicators. This catching up process has been particularly rapid not only in terms of Internet users and telephony (reflecting the worldwide diffusion of ICTs), but also with respect to innovative capabilities (patents and scientific articles), which is precisely the aspect where the technology-gap between the followers and the advanced clubs is more evident (see section 3). The only exception to this general trend of convergence refers to the tertiary enrolment ratio, whose technology-gap *vis-à-vis* the frontier has increased of around 14%, due to the very rapid increase of tertiary education in most advanced countries in the period.

When we turn the attention to the dynamics of the marginalized *vis-à-vis* the followers club, however, the picture is quite different. Here, convergence is rapid only in terms of Internet and telephony, and rather slow for all other indicators of technological infrastructures and education levels (i.e. electricity consumption, tertiary enrolment ratio, years of schooling and literacy rate). On the other hand, the innovation-gap between the marginalized and the followers clubs has significantly increased (patents: +24,7%; scientific articles: +16%), indicating that the group of marginalized economies has not been able to improve its innovative capabilities, while the other two groups have been very dynamic in this respect. This is in line with the finding of the Q-convergence analysis presented above, which suggests the existence of divergence and increasing polarization at the lower quantiles of the distributions of these two indicators.

This result is a reason of serious concern for the future of the world economy. Given that innovation is a key requirement to compete in the modern knowledge-based economy, the increasing polarization between rich and poor countries in terms of innovative capabilities may in fact lead to greater disparities in income and GDP per capita in the years ahead.

Table 5: σ-convergence and cluster convergence in the 1990s*

	σ-convergence			Cluster convergence	
	Coefficient of variation in 1990	Coefficient of variation in 2000	Rate of change	Advanced vs. Followers	Followers vs. Marginalized
Patents	3,01	2,73	-9,3%	-11,6%	+24,7%
Scientific articles	2,10	1,94	-7,6%	-19,0%	+16,0%
Internet users (1994 & 2000)	2,59	1,81	-30,1%	-53,0%	-94,0%
Fixed and mobile telephones	0,54	0,42	-22,2%	-17,7%	-29,6%
Electricity consumption	0,53	0,49	-7,5%	-4,0%	-3,4%
Tertiary S&E enrolment ratio	1,03	1,01	-1,9%	+13,8%	-12,9%
Mean years of schooling	0,58	0,54	-6,9%	-2,1%	-6,4%
Literacy rate	0,34	0,27	-20,6%	-2,6%	-11,7%

* The first two columns report the coefficient of variation in 1990 and 2000 respectively, where 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 over the 1990s. 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 from the levels of the technology-gaps in 1990 and 2000, reported in table 3 above.

5. Conclusions

In the last ten years, applied growth theory has developed rapidly. Empirical works have progressively moved away from the traditional cross-country regression framework, and, using a set of heterogeneous econometric methods, they have shown the existence of great differences in economic growth across different groups of countries (the convergence clubs) and of increasing polarization in income per capita between the rich and the poor clubs (so-called ‘emerging twin peaks’).

These recent empirical findings call for an explanation. The focus in growth theory has so far been on the rates of accumulation of physical and human capital, while the role of technology has frequently been neglected by the more recent empirical literature. This paper has argued that technology is a major factor to explain growth differences across countries, and that it is therefore important to explore how the recent empirical findings on clustering and polarization may be related to cross-country differences in the ability to create, imitate and implement new technologies. In particular, the purpose of the paper has been to study the existence, characteristics and dynamics of different *technology clubs* in the world economy.

The analysis has been empirical in nature, and it has made use of the ArCo database, that contains a set of indicators of technology for a large sample of 131 (developed and developing) economies for the period 1990-2000. Taking into account the complex and multifaceted nature of the concept of technology, the indicators that we have considered refer to several relevant aspects, such as the ability to create and to imitate new technologies, the level of technological infrastructures and the level of education and human skills.

Section 2 has presented the eight indicators used to measure these various aspects of countries’ technological capabilities. Many of these aspects, we have argued, represent strictly related and complementary dimensions of countries’ technological capabilities, and the relative indicators tend to be highly correlated. Therefore, the section has presented the results of a factor analysis, whose purpose has been to reduce this large set of indicators to a smaller group of distinct (uncorrelated) dimensions. The factor analysis has extracted two major factors: factor 1, a broad measure of technological infrastructures and human skills, and factor 2, representing the creation and diffusion of codified knowledge. While the former factor discriminates well among less advanced economies, the latter is better able to identify differences within the group of more advanced countries. Both factors have therefore been used to study cross-country differences in technological capabilities in our large sample of developing and developed economies.

Section 3 has presented the results of a hierarchical cluster analysis that has explored the existence of various groups of countries differing in terms of their levels of technological development. The results of the cluster analysis have proved to be robust to modifications in the clustering method, and stable over time between 1990 and 2000. They show the existence of *three* technology clubs characterized by very different levels of technology: (i) a restricted group of ‘advanced’ economies, characterized by high levels of technological infrastructures and human skills, and a great ability to innovate and to imitate; (ii) a cluster of ‘follower’ countries, with a medium level of technological infrastructures, medium-high human skills, and a low ability to innovate; (iii) a large group of ‘marginalized’ economies, characterized by low infrastructures and human skills, and a scarce ability to innovate and to imitate.

The characteristics of these technology clubs closely resemble those of the ‘innovation’, ‘imitation’ and ‘stagnation’ groups recently identified by Howitt and Mayer-Foulkes’ (2005) Schumpeterian model. The identification of these technology clubs is important, because it suggests that the existence of convergence clubs pointed out in the recent applied growth literature may be related not only to different initial conditions in terms of economic aspects, but also to cross-country differences in the ability to create, imitate and adopt new technologies.

A second reason of interest in these findings is that our analysis indicates the existence of two large technology-gaps in the world economy, and provides a measure of these gaps: the first refers to the great distance that separates the group of followers from the technological frontier, particularly in terms of innovative capabilities; the second refers to the impressive gap that separates the marginalized from the followers clubs, both in terms of innovative capabilities and of infrastructures and human capital. The existence of technology gaps is not by itself a surprising fact, but the quantification of these gaps provides a useful indication, particularly for technology-gap and Schumpeterian analytical growth models, where the dynamics of knowledge diffusion is dependent on the size of the technological distance (e.g. Verspagen, 1991; Howitt, 2000; Stokke, 2004; Howitt and Mayer-Foulkes, 2005).

Section 4 has then shifted the focus to the study of the dynamics of convergence and divergence among these technology clubs over the 1990s. The analysis in terms of β-and σ-convergence has shown that, for all of the indicators, an overall pattern of technological convergence has characterized the world economy in the 1990s. This catching up process and the related decrease in the dispersion of the technology variables has been particularly strong for the literacy rate, as well as for Internet users and telephony, thus suggesting that the rapid diffusion of ICTs have apparently not led to increasing disparities between rich and poor countries.

The concepts of β- and σ-convergence provide useful synthetic measures of the central tendency and variability of the world distribution of technology, but they do not make it possible to analyse the relative dynamics of different groups of countries. Therefore, in order to get a more precise characterization of the cross-country dynamics of technological change, we have proposed and used two new notions of convergence. One is Q-convergence, where the idea is to study β-convergence by estimating a set of quantile regressions for different percentiles of the technology growth distribution, instead of one single OLS regression as customary in the convergence literature. The other refinement is the notion of cluster convergence, which arises when, given a distribution partitioned into k clusters, the centre of a group gets closer to the centre of the upper cluster over time.

The analysis of Q- and cluster convergence has indicated that the technology clubs are characterized by very different patterns of technological change and catching up. The club of followers, in fact, has on the whole converged towards the technological frontier in terms of nearly all the indicators, including those measuring innovative capabilities (patents and articles) where its technology-gap was more evident at the beginning of the period. On the other hand, the club of marginalized countries has been able to catch up with respect to technological infrastructures and human skills (i.e. those variables related to the first principal component of the factor analysis), but not in terms of innovative capabilities (patents and articles, corresponding to the second principal component).

In other words, while the dynamics of infrastructures and skills (factor 1) has led to a process of convergence for both parts of the distribution, middle-income and poor economies, the dynamics of innovative capabilities (factor 2) has determined a pattern that closely resembles the popular twin-peaks result (Quah, 1996a, 1996b, 1996c): an increasing polarization between rich and poor countries, and a process of gradual catching up (or vanishing) of the middle-income group.

Innovation is a major engine of growth, and a key capability to compete in the modern knowledge-based economy. Thus, greater disparities in innovative activities between rich and poor economies might possibly determine increasing inequalities in income and GDP per capita in the near future. The relationship between twin-peaks in innovative capabilities and twin-peaks in income is an interesting topic for future research.

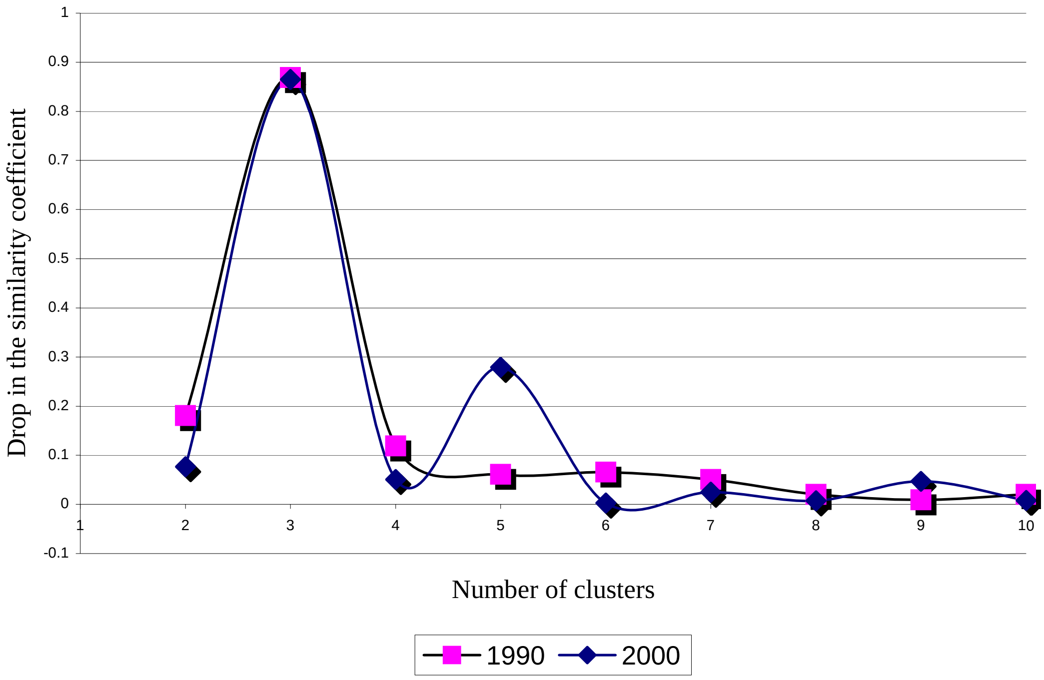
Appendix 1: Why three clusters?

Section 3 has presented the results of the cluster analysis, according to which there exist three major technology clubs with markedly different levels of technological development. Why has the cluster analysis identified just *three*, instead of, say, two, four, five or more groups of countries?

The clustering method that we have employed, the hierarchical agglomerative clustering algorithm, makes it possible to identify endogenously the number of groups that forms the best partition of the data. In hierarchical agglomerative cluster analysis, all the cases are initially treated as individual clusters. Then, at each step, the most similar cases are merged together according to the nXn similarity matrix. In the final step, all cases are merged into one large group. The sequence of mergers of clusters can be represented visually by a tree diagram, the *dendogram*. This makes it possible to identify the main clusters being formed at each step, their membership, and the right number of steps at which to evaluate the results. In fact, an *agglomeration schedule* records the similarity (or, put it differently, the distance) between the two clusters being merged at each step of the algorithm. The best partition of the data is the one corresponding to the highest drop in the similarity coefficient (or, analogously, to the greatest increase in the distance) between two successive steps.

Figure 2 represents the drop in the similarity coefficient as a function of the number of clusters (from 2 to 10) for our ArCo dataset, in both 1990 and 2000 (by using the between-groups method and the cosine distance measurement). The graph shows clearly that *three* is the number of clusters that maximizes the drop in the similarity coefficient, i.e. the one that forms the best partition of the data.

Figure 2: Drop in the similarity coefficient as a function of the number of clusters, 1990 and 2000 (between-groups method, cosine distance measurement).



Appendix 2: Cluster membership and its change over the 1990s*

Cluster 1: Advanced	Cluster 2: Followers	Cluster 3: Marginalized
	Asian	**Asian**
	← Hong Kong	← China
	← South Korea	← Indonesia
	← Singapore	← Vietnam
	Malaysia	Bangladesh
Established leaders	Philippines	India
Japan	Thailand	Mongolia
United States	Fiji	Nepal
		Papua New Guinea
Continental European	**Continental European**	Pakistan
Germany	← Austria	Sri Lanka
Netherlands	← Belgium	
Switzerland	← France	
United Kingdom	Luxembourg	
Northern European	**Southern European**	
Denmark	Cyprus	
Finland	Greece	
Iceland	Ireland	
Norway	Italy	
Sweden	Malta	
	Portugal	
Western offshoots	Spain	
Australia	Turkey	
Canada		
New Zealand	**Middle East**	**Middle East**
Israel	Bahrain	← Iran, Islamic Republic
	Jordan	← Oman
	Kuwait	Yemen, Republic
	Lebanon	
	Saudi Arabia	
	Syrian Arab Republic	
	United Arab Emirates	
	Latin American	**Latin American**
	Argentina	← El Salvador
	Bolivia	← Guyana
	Brazil	← Honduras
	Chile	Guatemala
	Colombia	Haiti
	Costa Rica	Nicaragua
	Dominican Republic	
	Ecuador	
	Jamaica	
	Mexico	
	Panama	
	Paraguay	
	Peru	
	Puerto Rico	
	Uruguay	

	Venezuela, RB	
	African	**African**
	South Africa	← Algeria
	Trinidad and Tobago	← Botswana
		← Mauritius
		← Tunisia
		← Zimbabwe
		Benin
		Cameroon
	Former socialist	Central African
	Armenia	Congo, Rep.
	Azerbaijan	Cote d'Ivoire
	Belarus	Egypt, Arab Rep.
	Bulgaria	Gabon
	Croatia	Ghana
	Czech Republic	Kenya
	Georgia	Lesotho
	Estonia	Madagascar
	Hungary	Malawi
	Kazakhstan	Morocco
	Kyrgyz Republic	Mozambique
	Latvia	Namibia
	Lithuania	Nigeria
	Macedonia, FYR	Senegal
	Moldova	Sudan
	Poland	Swaziland
	Romania	Tanzania
	Russian Federation	Togo
	Slovak Republic	Uganda
	Slovenia	Zambia
	Tajikistan	
	Turkmenistan	**Former socialist**
	Ukraine	← Albania
	Uzbekistan	

* The arrows indicate those countries shifting towards the upper cluster between 1990 and 2000

References

Abramovitz, M. 1986. “Catching-up, forging ahead and falling behind.” *Journal of Economic History* 46: 385-406.

Adelman, I., Morris, C. T. 1965. “A factor analysis of the interrelationship between social and political variables and per capita gross national product.” *Quarterly Journal of Economics* LXXIX: 555-578.

Anderson, G. 2004. “Making inferences about the polarization, welfare and poverty of nations: a study of 101 countries 1970-1995.” *Journal of Applied Econometrics*, 19: 537-550.

Archibugi, D. 1992. “Patents as Indicator of Technological Innovation”. *Science and Public Policy* 17: 357-368.

Archibugi, D., Coco, A. 2004a. “A new indicator of technological capabilities for developed and developing countries.” *World Development* 32 (4): 629-654.

Archibugi, D. and Coco, A. 2004b. “Measuring technological capabilities at the country level: A survey and a menu for choice.” *Research Policy*, 34 (2): 175-194.

Azariadis, C., Drazen, A. 1990. “Threshold externalities in economic development.” *Quarterly Journal of Economics* 1990: 501-526.

Barro, R., Lee, J. W. 2001. “International Data on Educational Attainment: Updates and Implications.” *Oxford Economic Papers* 53(3): 541-563.

Baumol, W. J. 1986. “Productivity growth, convergence and welfare: what the long-run data show.” *American Economic Review* 76 (5): 1072-1085.

Bernard, A. B. and Jones, C. 1996. “Technology and convergence.” *Economic Journal*, 106: 1037-1044.

Bianchi, M. 1997. “Testing for convergence: evidence from non-parametric multimodality tests.” *Journal of Applied Econometrics*, 12: 393-409.

Canova, F. 2004.: “Testing for convergence clubs in income per capita: a predictive density approach.” *International Economic Review*, 45 (1): 49-77.

Castellacci, F. 2006. “Theoretical convergence? A critical review of evolutionary and new growth theories.” *Journal of Economic Surveys*, forthcoming.

Cohen, W.M., Levinthal, D.A. 1989. “Innovation and learning: the two faces of R&D.” *Economic Journal* 99: 569-596.

Desai, M., Fukuda-Parr, S., Johansson, C., Sagasti, F. 2002. “Measuring the technology achievement of nations and the capacity to participate in the network age.” *Journal of Human Development* 3 (1): 95-122.

Desdoigts, A. 1999. “Patterns of economic development and the formation of clubs.” *Journal of Economic Growth*, 4: 305-330.

Durlauf, S. N., Johnson, P. A. 1995. “Multiple regimes and cross-country growth behaviour.” *Journal of Applied Econometrics* 10: 365-384.

Easterly, W. and Levine, R. 2001. “It’s not factor accumulation: stylized facts and growth models.” *The World Bank Economic Review*, 15 (2): 177-219.

Fagerberg, J. 1994. “Technology and International differences in growth rates.” *Journal of Economic Literature* 32: 1147-1175.

Fiaschi, D. and Lavezzi, A. M. 2003. “Distribution dynamics and nonlinear growth.” *Journal of Economic Growth*, 8: 379-401.

Gerschenkron, A. 1962. *Economic Backwardness in Historical Perspective*. Harvard University Press, Cambridge.

Giles, D. E. 2005. “Output convergence and international trade: time series and fuzzy clustering evidence for New Zealand and her trading partners, 1950-1992.” *Journal of International Trade and Economic Development*, forthcoming.

Giles, D. E. and Feng, H. 2005. “Output and well-being in industrialized nations in the second half of the 20th century: testing for convergence using fuzzy clustering analysis.” *Structural Change and Economic Dynamics*, 16: 285-308.

Gong, G. and Keller, W. 2003. “Convergence and polarization in global income levels: a review of recent results on the role of international technology diffusion.” *Research Policy*, 32: 1055-1079.

Hall, R. E. and Jones, C. 1999. “Why do some countries produce so much more output per worker than others?” *Quarterly Journal of Economics*, February 1999: 83-116.

Hobijn, B. and Franses, P. H. 2000. “Asymptotically perfect and relative convergence of productivity.” *Journal of Applied Econometrics*, 15: 59-81.

Howitt, P. 2000. “Endogenous growth and cross-country income differences.” *American Economic Review*, 90 (4): 829-846.

Howitt, P. and Mayer-Foulkes, D. 2005. “R&D, implementation and stagnation: a Schumpeterian theory of convergence clubs.” *Journal of Money, Credit and Banking*, 37 (1): 147-177.

Islam, N. 1999. “International comparison of total factor productivity: a review.” *Review of Income and Wealth*, 45 (4): 493-518.

Islam, N. 2003. “What have we learnt from the convergence debate?” *Journal of Economic Surveys* 17(3): 309-362.

ITU, International Telecommunications Union. 2001. *World Telecommunication Indicators,* ITU, Geneva.

Johnson, P. A. and Takeyama, L. N. 2001. "Initial conditions and economic growth in the US states." *European Economic Review*, 45: 919-927.

Jones, C. 1997. "On the evolution of the world income distribution." *Journal of Economic Perspectives*, 11 (3): 19-36.

Koenker, R. and Bassett, G. 1978. "Regression Quantiles." *Econometrica*, 46 (1): 33-50.

Koenker, R. and Hallock, K. F. 2001. "Quantile regression." *Journal of Economic Perspectives*, 15 (4): 143-156.

Lall, S., Albaladejo, M. 2001. *Indicators of the Relative Importance of IPRs in Developing Countries*. UNCTAD, Geneva, http://www.ictsd.org/unctad-ictsd/

Landes, D. 1969. *The Unbound Prometeus. Technological Change and Industrial Development in Western Europe from 1750 to the Present*. Cambridge University Press, Cambridge.

NSF, National Science Foundations. 2000, 2002. *Science and Engineering Indicators*. National Science Board, Washington, D.C.

Paap, R., and van Dijk, D. 1998. "Distribution and mobility of wealth of nations." *European Economic Review*, 42: 1269-1293.

Paap, R., Franses, P. H. and van Dijk, D. 2005. "Does Africa grow slower than Asia, Latin America and the Middle East? Evidence from a new data-based classification method." *Journal of Development Economics*, 77 (2): 553-570.

Pavitt, K. 1988. "Uses and Abuses of Patent Statistics", in: Van Raan, A. (Ed.), *Handbook of Quantitative Studies of Science and Technology*. Elsevier, Amsterdam.

Prescott, E.C. 1998. "Needed: A theory of total factor productivity." *International Economic Review*, 39 (3): 525-551.

Quah, D. 1993. "Galton's fallacy and tests of the convergence hypothesis." *Scandinavian Journal of Economics*, 95: 427-443.

Quah, D. T. 1996a. "Twin peaks: growth and convergence in models of distribution dynamics." *Economic Journal* 106: 1045-1055.

Quah, D. T. 1996b. "Convergence empirics across economies with (some) capital mobility." *Journal of Economic Growth* 1 (1): 95-124.

Quah, D. T. 1996c. "Empirics for economic growth and convergence." *European Economic Review* 40 (1996): 1353-1375.

Quah, D. T. 1997. “Empirics for growth and distribution: stratification, polarization, and convergence clubs. “ *Journal of Economic Growth* 2: 27-59.

Stokke, H. 2004. “Technology adoption and multiple growth paths: an intertemporal general equilibrium analysis of the catch-up process in Thailand.” *Weltwirtschaftliches*, 140 (1): 80-109.

Temple, J. 1999. “The new growth evidence.” *Journal of Economic Literature* XXXVII (March 1999): 112-156.

Temple, J., Johnson, P. A. 1998. “Social capability and economic growth.” *Quarterly Journal of Economics*, August 1998: 965-990.

UNDP. 2001. *Human Development Report. Making New Technologies Work for Human Development*. Oxford University Press, New York.

UNESCO. 2002. *World Education Indicators.* UNESCO, Paris, www.unesco.org

UNIDO. 2002. *Industrial Development Report 2002-2003. Competing through Innovation and Learning*. UNIDO, Vienna.

USPTO, United States Patent and Trademark Office. 2002. *Registered Patent Database.* USPTO, Washington, D.C., www.uspto.org

Verspagen, B. 1991. A new empirical approach to catching up or falling behind. *Structural Change and Economic Dynamics* 2: 359-380.

World Bank. 2003. *World Development Indicators*. The World Bank, Washington, D.C., www.worldbank.org