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Castellacci, Fulvio

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Fulvio Castellacci

Department of International Economics,
Norwegian Institute of International Affairs (NUPI),
POB 8159, Dep. 0033 Oslo, Norway
E-mail address: fc@nupi.no
Phone: +47-22994040

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Abstract

This paper looks at the convergence clubs literature from a Schumpeterian perspective, and it follows the idea that cross-country differences in the ability to innovate and to imitate foreign technologies determine the existence of clustering, polarization and convergence clubs. The study investigates the characteristics of different *technology clubs* and the growth trajectories that they have followed over time. The cross-country empirical analysis first explores the existence of multiple regimes in the data by means of cluster analysis techniques. It then estimates a technology-gap growth equation in a dynamic panel model specification. The empirical results identify three distinct technology clubs, and show that these are characterized by remarkably different technological characteristics and growth behavior.

JEL classification: O11; O33; O40

Keywords: Growth and development; Technological change; Convergence clubs; Polarization

1. Introduction

The cross-country convergence literature constitutes a large and engaging field of applied research. One major criticism that has recently been made to the standard convergence approach refers to the issue of cross-country *heterogeneity* (Temple, 1999; Durlauf et al., 2005). Heterogeneity is a problem for the standard OLS growth regression approach for two main reasons.

First, since country-specific effects are normally not included in the cross-section convergence equation, the omitted variable bias makes OLS estimates biased and inconsistent. The panel approach (fixed effects or dynamic model specifications) represents a relatively recent development in applied growth theory that overcomes this problem by including the full set of country-specific effects in the growth regression model (Islam, 1995; Caselli et al., 1996).

Secondly, the standard convergence equation assumes that the same law of motion applies to all the countries included in the sample, i.e. the slope of the regression line is assumed to be the same across countries. The convergence clubs approach is the strand of applied research that tries to overcome this second problem. It does this by exploring the existence of multiple regimes in cross-country data and by studying how the convergence dynamics differs across distinct convergence clubs (Durlauf and Johnson, 1995).

Both of these strands of applied research have led to a considerable progress in the study of heterogeneity and convergence across countries. However, most empirical studies in these approaches have so far made use of model specifications that are rooted in a neoclassical understanding of the growth process, which emphasizes the role of physical and human capital accumulation to explain the dynamics of convergence (or lack of such).

Technology has so far been neglected by these recent strands of empirical research. In the panel approach, technology is typically treated as an unobservable country-specific effect, so that its impact on the convergence process remains unexplained. In the convergence clubs approach, technology-related factors have also been largely neglected, since multiple equilibria have mostly been explained in terms of threshold externalities in the accumulation of physical and human capital (Azariadis and Drazen, 1990). One major challenge in the field of growth empirics is therefore to shed new light on the role of technology for the growth and convergence process by taking into account the recent developments in the applied study of cross-country heterogeneity.

Technology-gap models in the Schumpeterian tradition provide a natural theoretical framework to undertake this challenge. These models point out innovation and the international diffusion of technologies as major factors of growth and catching up (Nelson and Phelps, 1966; Abramovitz, 1986; Verspagen, 1991; Fagerberg, 1994). A recent class of endogenous growth models have refined this idea further and showed that multiple equilibria and convergence clubs can be explained as the outcome of cross-country differences in innovative ability and absorptive capacity (Howitt, 2000; Howitt and Mayer-Foulkes, 2005).

In line with the theoretical idea suggested by these models, this paper brings the Schumpeterian perspective into the empirical literature on heterogeneity and convergence clubs, and focuses on the role of innovation and technology diffusion for explaining the existence and the dynamics of country clubs. The purpose of the study is thus to investigate the existence, characteristics and growth behavior of different *technology clubs*. We want to analyse the extent of cross-country heterogeneity of technology, and to study how the technology-growth relationship differs across clubs.

The study is empirical in nature, and it considers a large sample of economies for the last three-decade period. The investigation of technology clubs requires an econometric methodology that is consistent with the recent advances in the heterogeneity and convergence literature mentioned above, and that is therefore able to investigate the existence of multiple regimes in the data and the distinct economic dynamics followed by the various clubs. The paper makes use of two complementary methods. The first part of the empirical study (section 3) explores the existence and the characteristics of different country clubs by making use of two distinct methods of cluster analysis, hierarchical agglomerative and classification and regression tree (CART) analysis.

The second part (section 4) studies the growth trajectories of these technology clubs over time by estimating a technology-gap equation rooted in the Schumpeterian growth model. This econometric analysis makes use of a dynamic panel model specification, whose main advantage is to simultaneously take into account the heterogeneity issue as well as the possible endogeneity of the explanatory variables.

The econometric results give basic support to the main idea investigated by the paper, and point out the existence of three technology clubs, which greatly differ in terms of their levels of technological development, the dynamics of technological change, and the growth trajectories that they have followed over time.

2. Schumpeterian growth models and the convergence clubs

The convergence clubs hypothesis has increasingly attracted the attention of growth theorists in the last decade. According to this hypothesis, countries that are similar in terms of structural characteristics but differ in their initial conditions converge to different steady states (Galor, 1996). The study of convergence clubs was greatly inspired by the seminal contribution of Durlauf and Johnson (1995). Their empirical study investigated the existence of multiple regimes and nonlinearities in the growth process by dividing countries into four groups according to their initial conditions, measured by the initial level of GDP per capita and the literacy rate. These four clusters, identified through a regression tree analysis, were shown to follow well distinct growth trajectories, thus supporting the hypothesis of the existence of multiple growth regimes.

This study was subsequently followed and refined by a set of recent empirical works, which aimed at identifying the characteristics and dynamics of convergence clubs by making use of a variety of econometric techniques and by focusing on different types of initial conditions (Desdoigts, 1999; Hobijn and Franses, 2000; Johnson and Takeyama, 2001; Fiaschi and Lavezzi, 2003; Canova, 2004; Paap et al., 2005).

What are the theoretical mechanisms that may explain these empirical findings on clustering, polarization and convergence clubs? One common answer, pointed out by multiple equilibria models, is related to threshold externalities in the accumulation of physical and human capital (Azariadis and Drazen, 1990). One alternative explanation has more recently been put forward, which, instead of focusing on the process of capital accumulation, points out the crucial role of technological change for the existence and the dynamics of convergence clubs.

Technology is a main source of economic development and a major factor to explain growth differences across countries (Bernard and Jones, 1996; Prescott, 1998; Hall and Jones, 1999; Islam, 1999; Gong and Keller, 2003).[1] Economic historians have long ago argued that developing countries may exploit their backwardness position by

[1] For a recent overview of different strands of research studying the relationship between innovation, technology diffusion and economic growth, see Castellacci (2007).

imitating and adopting new technologies produced in advanced economies. However, they have also shown that the process of imitation is costly, and that it requires the existence of technological capabilities that many developing countries lack (Gerschenkron, 1962; Landes, 1969; Abramovitz, 1986).

In this framework, the basic reason for the existence of different clubs is that countries greatly differ in terms of their technological capabilities and, hence, in terms of their ability to catch up by imitating foreign advanced technologies. Countries characterized by greater levels of technological development are better able to catch up and to converge gradually towards the club of advanced economies, while countries with lower capabilities find it harder to exploit the scope for catching up, and so risk of falling further behind.

This idea has recently been presented in a more rigorous analytical framework by Schumpeterian multiple equilibria endogenous growth models. According to these, cross-country differences in the ability to support and to foster a productive R&D sector, as well as differences in the capability to imitate foreign advanced technologies, lead to clustering, increasing polarization and the existence of convergence clubs. For countries below the technological frontier, the existence of a technology gap provides opportunities for catching up by exploiting the international diffusion of advanced technologies, but this potential can only be realized if a national economy has a sufficient level of absorptive capacity. If absorptive capacity is too low (below a minimum threshold level), the opportunities related to the imitation-based catching up process will not be exploited.

Various analytical models in the Schumpeterian tradition have formalized and refined this main idea. An early seminal contribution is the model by Nelson and Phelps (1966), which assumes an exponential diffusion mechanism where absorptive capacity is affected by the level of human capital. Inspired by this original formulation, more recent models have built upon this technology-gap formulation and made use of a logistic type of catching up function, e.g. Verspagen (1991), Castellacci (2002), Papageorgiou (2002), Stokke (2004) and Benhabib and Spiegel (2005).

Howitt (2000) and Howitt and Mayer-Foulkes (2005) have refined the Schumpeterian growth model by arguing that cross-country differences in the rates of return to investments in human capital may shape the dynamics of absorptive capacity and thus generate three distinct convergence clubs: an *innovation*, an *implementation* and a *stagnation* group. The first is rich in terms of both innovative ability and absorptive capacity. The second is characterized by a much lower innovative capability, but its absorptive capacity is developed enough to enable an imitation-based catching up process. The stagnation group is instead poor in both aspects, and its distance *vis-à-vis* the other two groups tends to increase over time. Acemoglu et al. (2006) have refined the club model by arguing that a crucial source of dynamics for countries in the *innovation* group is constituted by the availability of a skilled pool of managers and entrepreneurs. The competition and selection process through which skilled managers emerge represents a crucial growth mechanism for countries that are already close to the technological frontier.

Galor and Weil (2000) and Galor (2005) have proposed similar formulations where the interaction between human capital and technological change generates different convergence clubs. Consistent with previous contributions, the main idea of these models is that technological progress increases the return to investments in human capital, and the latter does in turn enhance and accelerate the process of technological change. According to these models, this simple interaction mechanism may explain the long-run transformations from a *Malthusian* growth regime, to a *sustained* growth regime and then to a *modern* growth regime. Convergence clubs are then explained as the outcome of different timing of transitions experienced by national economies in the long-run.

In brief, a Schumpeterian model of convergence clubs can be summarized by means of the following main propositions. (1) The *technology gap* provides opportunities for catching up through the imitation of foreign advanced technologies. (2) The ability to exploit these opportunities depends on the *absorptive capacity* of a country. Countries will only catch up if their absorptive capacity is above a minimum threshold level. (3) The absorptive capacity is greatly affected by the level of *human capital*. The latter does not simply have a direct effect on growth (as a production factor) but also an indirect effect by enabling imitation and technological catching up. (4) The *innovative ability* of a country is the other major growth factor. (5) Different levels of absorptive capacity and innovative ability determine what *country club* each national economy belongs to in any given period, hence they determine whether a country will be able to catch with the technological frontier or fall behind.

These theoretical propositions lead to formulate the two general hypotheses that will guide our empirical analysis.

Hypothesis 1: Technology clubs. There exist various country groups characterized by different levels of absorptive capacity and innovative ability. Rich countries perform well in terms of both aspects. Middle-income countries have low innovative ability but relatively high absorptive capacity. Less developed economies are poor in both aspects.

Hypothesis 2: Growth trajectories. Innovative ability and absorptive capacity are crucial factors of growth and catching up. However, the growth effects of innovative ability and absorptive capacity (and other related factors) greatly differ across the technology clubs.

Section 3 will investigate the empirical relevance of the first hypothesis, and section 4 will then examine the second one.

3. Technology clubs and gaps: data and descriptive evidence

The first part of our empirical analysis investigates the existence of technology clubs in the world economy, and points out their characteristics and the technological distance that separates them. The descriptive analysis makes use of a set of indicators of technological capabilities for a large sample of 149 economies. Data for such a large sample of countries are only available for a more recent time span, so this first part of the analysis focuses on a relatively short period, spanning from the beginning to the end of the 1990s.

The set of indicators measure different aspects of countries' technological capabilities. Appendix 1 reports the definition and source of the data and indicators. The *innovative ability* is measured by means of two indicators, the number of patents and the number of scientific articles per capita.[2] The *absorptive capacity* is measured by looking at two interrelated aspects: first, the level of human capital (literacy rate, secondary schooling, higher education); secondly, technological infrastructures,

[2] R&D would have been another useful indicator of innovative activity, but it has not been used here because its country coverage is much more limited than it is the case for the other two variables.

referring to both old (fixed telephony, electricity) and ICT infrastructures (computers, Internet).

We want to explore cross-country differences in terms of these factors and identify groups of countries characterized by distinct levels of innovative ability and absorptive capacity. We make use of cluster analysis techniques to achieve this objective.[3] In general terms, the purpose of cluster analysis is to explore the group-structure of a dataset and identify distinct groups of observations (clusters) in such a way that observations are relatively homogenous within each group but differ substantially across clusters.

The two key dimensions along which we seek to identify and characterize country groups are, in line with the Schumpeterian growth model discussed in section 2, the innovative ability and the absorptive capacity of national economies.[4] In the cluster analysis, the innovative ability is measured by means of the number of scientific articles per capita, whereas the absorptive capacity is measured through the literacy rate. These two indicators have been selected as the discriminatory factors in the cluster analysis for two reasons: first, they are the variables that have the widest country coverage, whereas most of the other indicators are only available for a somewhat more limited sample of countries; secondly, they represent well distinct dimensions of the catching up process and, taken together, they are able to account for a large portion of cross-country variability for both industrialized as well as less developed economies.

[3] Recent empirical studies in the convergence clubs literature have also made use of various clustering methods to point out the existence of different country groups (Desdoigts, 1999; Hobijn and Franses, 2000; Canova, 2004; Paap et al., 2005). Castellacci and Archibugi (2008) have made use of a combination of factor and cluster analyses to study cross-country differences in technological capabilities. The latter study focuses on the distribution of knowledge across nations, but it does not investigate the implications for economic growth and catching up.

[4] In a Schumpeterian growth context, these two dimensions represent *initial conditions* that differ across countries, and which lead different groups of economies to converge to distinct steady states (Howitt, 2000).

Figure 1 reports the kernel density estimates for these variables in 1990 and 2000 respectively.[5] The literacy rate is a simple and widely used measure of basic human skills, and it is a necessary precondition for the subsequent development of an advanced human capital base. The kernel density graph shows that the cross-country distribution of the literacy rate is skewed, and that it varies significantly within the large group of less developed economies. On the other hand, the number of scientific articles per capita is a measure of countries' innovative ability, which represents a key requirement for economies that seek to catch up with the technological frontier. Its cross-country distribution is also quite skewed, since innovative capabilities differ substantially within the group of industrialized economies. Taken together, these two factors represent therefore two distinct dimensions of countries' technological capabilities that are both relevant to investigate cross-country differences in our large sample of developing and developed economies.

< Figure 1 here >

The clustering technique we use is a combination of hierarchical cluster analysis and classification and regression tree (CART) analysis. The first step is to carry out a hierarchical cluster analysis, which is a technique where different groups of observations (clusters) are progressively combined together on the basis of their similarity in terms of the two input variables. The iterative algorithm makes it possible to identify the number of clusters that forms the best partition of the dataset, i.e. the number of clusters are identified *endogenously* and not imposed *ex-ante*. The second step of our clustering exercise is to make use of classification and regression

[5] In the computation of the kernel density estimates, as well as in the subsequent cluster analysis, the two factors have been entered in standardized form. On the use of different methods of standardization in the study of the world distribution of income, see Bianchi (1997, pp. 398-400).

tree techniques (CART) in order to check the robustness of the hierarchical analysis results, and to identify the threshold values of the input variables that determine what club each country belongs to (Durlauf and Johnson, 1995). Further details on these methods of cluster analysis are reported in Appendix 2.

The clustering exercise has been repeated for data referring to two distinct years, 1990 and 2000, in order to assess the robustness and the stability of the results over time. Figure 2 reports the results of the CART analysis for 1990 and 2000. In both years, the results identify *three* main technology clubs (for a complete list of countries included in each cluster, see Appendix 3). The three-club partition turns out as the most efficient result in both 1990 and 2000, and this result is robust to changes in the clustering methods used.

The first technology club is composed by a group of around 50 *marginalized* countries, whose literacy rate is lower than 66% (70%) in 1990 (2000). All the other countries in the sample, which score above this threshold level of the literacy rate, are further split into two groups according to their level of innovative ability. The second club is composed of a large bunch of nearly 90 *followers* countries, whose number of scientific articles per million people is lower than 340 (346) in 1990 (2000). Above this threshold level, countries are classified as *advanced*, a club that comprises a restricted group of less than 20 rich economies around the technological frontier.

< Figure 2 here >

Table 1 reports the major technological characteristics of these three technology clubs, as well as a measure of the technological distance that separates them. The *advanced club* is relatively small, accounting for only about 13% of the sample's population. In both 1990 and 2000, countries around the technological frontier are characterized by very high levels of technological development with respects to both of the aspects we are focusing on, the absorptive capacity (measured by human capital levels and technological infrastructures, including ICTs) and the innovative ability (measured through scientific articles and patents per capita).

The *followers club* accounts for a much larger share of the sample's population (around 55%), and it comprises economies from the South of Europe, the Middle East, Latin America, East Asia and the Former Socialist block. In terms of technological infrastructures and human capital, these countries are not so distant from the technological frontier. The magnitude of their absorptive capacity gap *vis-a-vis* the advanced club is comparable to their distance in terms of GDP per capita (with the exception of ICT infrastructures, where the size of the gap is much larger). The aspect where the followers club lags more strikingly behind is its low level of innovative capabilities, since the gap is more than 10:1 in terms of scientific articles, and more than 30:1 when measured by patents.[6]

The *marginalized club* accounts for more than one third of the sample's population, and it includes the least technologically developed economies of the world, mostly from South and East Asia, Central America and Africa. The magnitude of the gap is striking with respect to all of the technology indicators considered. The last two rows of table 1 show in fact how large the technological distance is between the followers and the marginalized countries, particularly in terms of some crucial aspects that constitute key requirements to catch up in the modern knowledge-based economy: the

[6] It is interesting to observe that this cluster comprises, besides the large number of middle-income economies, also three rich countries such as Italy, Luxembourg and Hong Kong. These countries, despite their high income levels, are characterized by a quite low number of scientific articles per capita, much below the threshold levels identified by the CART analysis (340 in 1990 and 346 in 2000). This explains why these countries turn out to be part of the followers rather than the advanced club.

gap is nearly 6:1 for the tertiary enrolment ratio, around 15:1 for the indicators of traditional technological infrastructures (telephones and electricity consumption) and scientific articles, and up to 223:1 in terms of patents per capita.

These empirical results, pointing to the existence of three technology clubs and of two large technology-gaps that separate them, are in line with and provide support for the recent class of Schumpeterian endogenous growth models that were outlined in section 2. The characteristics of our technology clubs, in particular, closely resemble the properties of the *innovation*, *imitation* and *stagnation* groups identified by Howitt and Mayer-Foulkes' (2005) recent model. This provides support for our first main hypothesis (see end of section 2). *Advanced* countries perform well in terms of both innovative ability and absorptive capacity. *Follower* countries have low innovative ability but relatively high absorptive capacity. *Marginalized* economies are poor in both aspects.

The three technology clubs do not only differ in terms of their levels of technological development, but also with respect to the dynamics of technological change over time. In fact, by comparing the technology-gaps at the beginning and at the end of the 1990s (lower part of table 1), it is possible to see that: (1) the *advanced* countries around the technological frontier have grown rapidly, making the catching up process of follower countries more demanding over time; (2) the *followers* club has on the whole been able to activate a slow process of catching up and to close gradually its technology gap in terms of all of the indicators considered (with the only exception of the tertiary enrolment ratio, for which the technological distance has increased); (3) the *marginalized* group has experienced a slow process of catching up in terms of its level of technological infrastructures and human capital (absorptive capacity), but its technology-gap *vis-a-vis* the other clubs has significantly widened with respect to the innovative ability (scientific articles and, particularly, patents per capita).

Since imitation and innovative capabilities are key requirements to compete in the modern knowledge-based economy, we may expect that the different levels of technological development and the distinct dynamics of technological change described in this section may have been important factors to determine different trajectories in the growth of income and GDP per capita of the three technology clubs. This leads us to the second part of the empirical analysis.

< Table 1 here >

4. Growth trajectories, 1970-2000

The second hypothesis investigated by our empirical analysis focuses on the growth trajectories followed by the technology clubs. The Schumpeterian technology-gap model outlined in section 2 argues that innovative ability and absorptive capacity are crucial factors of growth and catching up. However, the club structure generated by this type of model also suggests that the growth effects of innovative ability and absorptive capacity (and other related factors) may greatly differ across the technology clubs.

The econometric investigation of this hypothesis makes it necessary to consider three relevant aspects. First, it is important to carry out this type of analysis by considering a longer time span than the one on which the previous section has focused. Thus, instead of only looking at the 1990s, we estimate our Schumpeterian growth model for the longer period 1970-2000. This extension is necessary in the context of growth empirics, although the obvious drawback is that the size of the cross-country sample reduces to around 70 countries, since data for several countries are not available for the period prior to the 1990s.

Secondly, it is important to make use of an estimation method that carefully takes into account the problem of cross-country *heterogeneity*. In the presence of heterogeneity across national economies, the assumption that the individual (country-specific) effect must be uncorrelated with the other regressors is violated. The reason is that country-specific effects (e.g. related to institutional or technology differences) are likely to be correlated with some of the right-hand-side variables of the growth equation, typically the initial level of GDP per capita and the human capital level. For this reason, the omitted variable bias makes OLS estimates inconsistent and upward biased. This problem can be overcome in a panel (fixed-effects) specification, where the full set of country specific effects is included in the regression model (Islam, 1995).

Thirdly, it is reasonable to assume that (at least some of) the explanatory variables in the regression model are endogenous. This is something that it is sensible to expect in the context of a Schumpeterian growth model, since the main explanatory factors, innovative ability and absorptive capacity, cannot be regarded as exogenous variables but rather co-evolve with the other explanatory factors as a national economy grow richer. In the recent applied growth literature, the endogeneity problem is frequently taken care of by estimating a dynamic panel model specification of the convergence equation (Caselli et al., 1996).[7] In Arellano and Bond (1991) GMM estimator, explanatory variables are treated as endogenous, and their lagged levels are used as instruments for the lagged first differences.

[7] In this *Journal*, see also the works of Amable (2000) and Peneder (2003).

Taking into account these aspects, our econometric exercise estimates the Schumpeterian growth model for the period 1970-2000 by making use of a dynamic panel model specification, which simultaneously takes care of the heterogeneity and endogeneity problems. The model specification is outlined as follows. The standard cross-country growth regression can be written as:

$$\Delta Y_{i,t} = ß \ln Y_{i,t-1} + \Psi \mathbf{X}_{i,t-1} + \alpha_i + \mu_t + \varepsilon_{i,t} \tag{1}$$

where $Y_{i,t-1}$ is the level of GDP per capita at the beginning of the period; $\mathbf{X}_{i,t-1}$ is a vector of explanatory variables that condition the convergence process; α_i is a country-specific effect; μ_t is a time-specific effect; the indexes i and t indicate country and time respectively. The equation can be rewritten in levels as:

$$\ln Y_{i,t} = (1+ß)\ln Y_{i,t-1} + \Psi \mathbf{X}_{i,t-1} + \alpha_i + \mu_t + \varepsilon_{i,t} \tag{2}$$

By first differencing equation 2, we eliminate the country-specific effect α_i and obtain the growth equation specified in first differences:

$$\Delta \ln Y_{i,t} = (1+ß)\Delta \ln Y_{i,t-1} + \Psi \Delta \mathbf{X}_{i,t-1} + \Delta\mu_t + \Delta\varepsilon_{i,t} \tag{3}$$

The vector of explanatory variables **X** contains the following variables that characterize the Schumpeterian growth model (see Appendix 1 for a definition and source of the data and indicators):

- The innovative ability, measured through patents and scientific articles per capita.[8]
- The absorptive capacity, referring to two related aspects: (1) technological infrastructures (traditional and ICT-related infrastructures); (2) human capital, measured by the indicators of secondary and higher education respectively.
- A catching up factor, measured through an interaction variable specified as the product of the technological distance from the frontier (GAP) and the absorptive capacity (measured by means of the higher education variable). This interaction variable (GAP·Higher) provides a stylized measure of the non-linear catching up process assumed by Schumpeterian growth models with multiple equilibria, since the imitation and catching up process is expected to be more rapid when the potential provided by a large technology-gap can be exploited by means of a well-developed absorptive capacity (Benhabib and Spiegel, 1994; 2005).
- A set of other customary regressors that are commonly regarded as important factors to explain growth differences across countries, and in particular: (1) physical capital accumulation (investment share of GDP); (2) trade (exports as a share of GDP); (3) the industrial structure (industry and service shares of GDP).
- The GDP per capita. This is the lagged level of the dependent variable in the panel dynamic model specification. Notice that since the ß coefficient in equation (1) is usually expected to be negative (in the presence of cross-country convergence), when the growth equation is specified as in equations (2) or (3) above the

[8] As previously pointed out, R&D would have also been an important variable to use in our cross-country study. However, the availability of R&D data is more limited than for the indicators of patents and scientific articles. In particular, R&D data are available for a relatively large number of countries (e.g. from UNESCO or the World Bank) only for a more recent period, but not in panel form for the longer period 1970-2000 that we are considering here. For this reason, we have not been able to use this variable in our cross-country panel analysis.

estimated coefficient is instead expected to be positive (and smaller than 1, in the presence of convergence).

Equation (3) is estimated by means of Arellano and Bond GMM estimator. As customary in the panel growth approach, all the variables are averages over 5-year periods (the whole estimation period, 1970-2000, is therefore composed of six 5-year periods). All variables are lagged one period and treated as endogenous, and their lagged levels are used as instruments for the lagged first differences.

Tables 2 and 3 present the estimation results. Table 2 reports the results of the base version of the model. The estimations in columns 1 and 2 refer to the whole period 1970-2000, whereas those in columns 3 and 4 focus on the shorter span 1985-2000, where we also have data availability for the scientific articles per capita and the ICT infrastructures variables (which are not available for the period prior to 1985).

Table 3 reports the results of a piecewise linear specification of the model, where the slopes of the regression lines are allowed to differ across the technology clubs. The use of slope dummies makes it possible to investigate differences in the estimated coefficients among the three country groups, and therefore to identify the most relevant catching up factors for each of them. Thus, the model in table 3 does not only overcome the heterogeneity issue by including country-specific effects as standard in a panel data context (different intercepts), but also by allowing non-linearities and between-club differences in the growth process (different slopes). The tests reported at the bottom of the tables confirm the validity of the instruments (Sargan test) as well as the absence of second-order autocorrelation.

< Table 2 and table 3 here >

The investment variable is positive and significant in the regressions in table 2. Table 3 indicates the existence of substantial differences across countries in the role of physical capital accumulation. The estimated coefficient for the investment variable is in fact quite large in the advanced club, much lower for the followers group, and not statistically significant for the marginalized club.[9]

The trade variable does also reveal considerable cross-country differences. The results in table 2 are not conclusive, since the coefficient is negative for the longer period and positive for the shorter time span. Table 3 suggests however that the positive growth effect of trade can mostly be attributed to countries in the followers club, whereas the effect is negative for economies in the marginalized group. Trade does therefore turn out to be a relevant development channel to the extent that countries are characterized by a minimum (threshold) level of absorptive capacity, below which they do not seem to be able to exploit the technological and economic opportunities provided by greater economic integration (Amable, 2000; Papageorgiou, 2002).[10]

Turning to the role of industrial structure and structural change for economic growth, the variable measuring industry as a share of GDP turns out to be positive and significant in some of the regressions but it is not precise in others. The industry share appears to be a relevant development factor for countries in the marginalized group. Similarly, the service share variable points out this factor as particularly important in the context of less developed economies. These results confirm the important role of structural change for economic growth (Fagerberg and Verspagen, 2002; Peneder,

[9] This pattern is in line with the results obtained by Durlauf and Johnson (1995) in a cross-sectional sample. Their estimation results did in fact indicate that the coefficient of the investment variable is higher (and more significant) for the group of advanced countries, and lower (and less significant) for the larger group of less developed economies (i.e. their group "2", see table V, p. 375).

[10] This result is consistent with existing empirical evidence. See the comprehensive overviews of Vamvakidis (2002), Lewer and Van de Berg (2003) and Darity and Davis (2005).

2003), and indicate that the upgrade and transformation of the industrial structure is a relevant growth engine particularly for developing countries.

The innovation variables turn out to be positive and highly significant in all the regressions reported in table 2, thus confirming the importance of the innovative ability factor in the Schumpeterian growth model. The patents indicator is positively related to GDP per capita, and the regressions in table 3 show that this effect is particularly strong and statistically precise for the followers club. The scientific articles variable, which is only available for the shorter period 1985-2000, is also positively related to economic growth. This positive estimated effect is significant for both the followers and the marginalized group, and the coefficient is stronger for the latter. These results are indeed consistent with the descriptive evidence presented in section 3. The followers and marginalized clubs have on average a much lower innovative ability than the advanced group, so that any small increase in innovative activities for these catching up economies is able to generate considerable income growth.

Let us turn the attention to the set of variables investigating the role technological infrastructures. Traditional infrastructures are represented by electricity and fixed telephony. The electricity variable is positive and significant in the regressions in table 2. The piecewise linear version of the model in table 3 suggests however that this indicator has a significant effect for the followers club but not for the others. The telephony variable is also positively related to income growth, as expected, and this relationship is particularly strong (and more significant) for the marginalized group of economies. Traditional technological infrastructures thus appear to be more relevant catching up factors for countries that are far below the technological frontier, representing one of the basic aspects that contribute to define the absorptive capacity and imitation capability of developing economies.

ICT-related infrastructures, on the other hand, turn out to be a more relevant growth engine for advanced countries. The computers and Internet users per capita variables are only available for a shorter time period (see columns 3, 4, 7 and 8). The Internet indicator does not lead to stable and conclusive results: it turns out with a negative estimated coefficient in table 2, but the results in table 3 are not significant at conventional levels. The computers per capita indicator takes instead the expected positive sign in both tables 2 and 3. It is the advanced club of countries that drives this result, since the positive relationship between computers and GDP per capita is much stronger and more significant for the rich group than the others.

The other important aspect that contributes to define absorptive capacity is, in line with the Schumpeterian literature, human capital. In technology-gap models with multiple equilibria, human capital does not only have a direct effect on economic growth (as a production factor) but an indirect effect as well, since it fosters the absorptive capacity and imitation capability of catching up economies. First, we look at the results for the secondary education variable, which show an interesting pattern. The variable has a negative sign in the regressions in table 2, similarly to what previously found and discussed in the applied growth literature (e.g. Benhabib and Spiegel, 1994; Pritchett, 2001). However, in the piecewise linear version of the model the estimated coefficient is positive and significant for the followers club (and not precise for the other groups).

Secondly, the effect of the higher education variable is also influenced by between-club differences. The negative estimated coefficient in table 2 is mostly attributable to the dynamics of followers and marginalized economies, whose knowledge-gap in terms of higher education *vis-à-vis* the frontier has enlarged over time. These clubs show a negative estimated coefficient in the regressions in table 3, whereas the relationship between higher education and growth is positive and strong for countries in the advanced club (see columns 5 and 7).

The indirect effect of human capital on growth (through its impact on absorptive capacity and imitation capability) is measured by means of the interaction factor (GAP·Higher). This catching up factor has a positive and significant estimated coefficient in table 2 (see columns 2 and 4), thus confirming the relevance of this interaction mechanism, which indicates that catching up countries with a relatively high advanced human capital base have been better able to exploit the opportunities provided by their backward position through the imitation of foreign advanced technologies (Verspagen, 1991; Benhabib and Spiegel, 2005). It is also interesting to observe that this interaction effect varies considerably among the three country groups. The magnitude of the estimated coefficient is in fact much larger for the advanced club than for the other two country clusters (see table 3, columns 7 and 8). This corroborates the idea that the imitation-based catching up process is more effective for countries that are characterized by a high absorptive capacity, and suggests that the rapid growth of higher education that rich countries have experienced in recent decades has been an important source of economic dynamics for the industrialized world.

Summing up, the estimation results provide empirical support for the class of technology-gap models with multiple equilibria that have recently been developed within the Schumpeterian approach (e.g. Howitt, 2000; Howitt and Mayer-Foulkes, 2005). Our second main working hypothesis (see end of section 2) is hence corroborated by the econometric results. The innovative ability and the absorptive capacity of national economies are crucial factors of growth and catching up, in combination with other important factors that condition the catching up process. However, the growth effects of innovative ability and absorptive capacity (and other related factors) differ substantially across the technology clubs.

In the *advanced* club, the most important growth variables turn out to be the investment share of GDP, the innovative ability (both patents and scientific articles), ICT infrastructures (computers per capita), the higher education level, and the catching up (interaction) variable.

For countries in the *followers* group, significant catching up factors are represented by physical capital accumulation, the export share of GDP, innovation (particularly patents), traditional infrastructures, and human capital (secondary education has a direct positive effect, whereas higher education has an indirect effect measured through the catching up interaction variable).

In the *marginalized* club, economic development is negatively related to the openness of the economy, and positively related to the structural change variables (industry and services shares of GDP), innovative activities undertaken by the public science system (articles), and traditional infrastructures (fixed telephony). The growth effect of human capital is mostly indirect as measured by the catching up interaction effect.

5. Conclusions

This paper has proposed an empirical contribution to the convergence club literature. The main interest of the latter, in a nutshell, is to show that countries that differ in terms of initial conditions tend to converge to different steady states (Durlauf and Johnson, 1995; Galor, 1996). Inspired by the various recent empirical studies in this field, the paper has departed from them by focusing more explicitly on the role of technology for the process of growth and development.

In line with recent Schumpeterian multiple equilibria growth models (section 2), the paper has argued that the capability to imitate foreign advanced technologies and the ability to innovate are crucial factors to explain the existence of clustering, polarization and convergence clubs. Following this main idea, the paper has looked at the convergence clubs empirical literature from a Schumpeterian perspective, and it has investigated the existence, characteristics and growth trajectories followed by different technology clubs.

The cross-country empirical analysis has followed two steps. The first one (section 3) has investigated the existence and characteristics of different technology clubs by making use of two distinct methods of cluster analysis, hierarchical agglomerative and classification and regression tree (CART) analysis. The second one (section 4) has studied the economic performance of these technology clubs over a longer time period (1970-2000) by estimating a technology-gap growth equation in a dynamic panel model specification.

The econometric results give basic support to the main hypotheses investigated by the paper. In a nutshell, the main finding of the study is that there exists three technology clubs, which greatly differ in terms of their levels of technological development, the dynamics of technological change, and the economic growth trajectories that they have followed during the last three decades.

The *marginalized club* is characterized by low levels and a sluggish dynamics of both innovative ability and absorptive capacity. Its economic growth performance has also been modest in comparison to the other two groups, and it has mainly been based on three major factors that constitute crucial requirements to enable the process of imitation of foreign advanced technologies. These factors are the process of structural change from primary to industrial and service activities, the building up of basic technological infrastructures (fixed telephony), and the human capital level (whose growth effect is mostly indirect through its impacts on the absorptive capacity). Innovative activities carried out by the public science system are also positively related to the economic development process, representing a relevant precondition for the subsequent development of advanced innovative capabilities in the private sector.

On the other hand, less developed economies have not been able to exploit the opportunities provided by economic globalisation, and the overall effect of trade on development has been negative. The main challenge ahead for these countries is therefore to strengthen and accelerate the development of a solid industrial and technological infrastructure and a strong human capital base, which constitute necessary requirements for exploiting the emerging opportunities provided by the increasing patterns of trade and the related process of international diffusion of technologies.

The *followers club* lags also well behind the technological frontier in terms of innovative capabilities, but its level of absorptive capacity is much greater than in the marginalized group. This club has on average been able to activate a slow process of technological and economic catching up over time, and its growth trajectory has been based on the following main factors.

Investments and exports dynamics represent a first set of important factors to explain the growth performance of this country group. Absorptive capacity constitutes a second crucial aspect. In fact, the building up of traditional technological infrastructures (electricity and fixed telephony) and the dynamics of human capital are both related to the growth trajectory of follower countries. With respect to human capital, secondary education is positively related to GDP per capita growth, whereas higher education has an indirect effect through its impacts on absorptive capacity and the imitation process. Another relevant factor to explain growth differences within this country group is the innovative ability (particularly patents), whose level is however still quite low in comparison to the most technologically advanced economies. The further development of innovative capabilities certainly constitutes an important challenge ahead for middle-income countries that seek to catch up with the technological frontier.

Finally, the *advanced club* comprises a restricted set of economies that are characterized not only by a strong human capital base and a well-developed web of technological and economic infrastructures, but also by a great capability to produce new advanced technologies. Over time, this group has experienced a very dynamic trajectory of both technological change and economic growth, and it has been able to take full advantage of the new opportunities provided by the ICT-based general purpose technologies and by the increasing patterns of trade flows. Such a dynamic growth trajectory has been based on four main factors.

The first is the embodied technological progress related to investments in advanced capital equipments. The second is the building up and rapid use of advanced technological infrastructures related to ICTs (particularly computers). The third is the growth of tertiary education, which has been a crucial factor to shape the dynamics of absorptive capacity and support the growth and catching up process. The fourth is the rapid pace of innovative activities carried out by the public science system as well as the private sector. The further development of advanced infrastructures, human skills and innovative capabilities arguably constitutes a key policy requirement for industrialized economies that seek to maintain and improve their competitive position.

Appendix 1: Definition and source of the indicators used

Model variable	Indicator	Definition	Source
Innovative ability	Patents	Patents registered at the USPTO per million people	USPTO (2002)
	Articles	Scientific articles per million people	WDI*
ICT infrastructures	Internet	Internet users per thousand people	WDI
	Computers	Number of computers per thousand people	WDI
Traditional infrastructures	Telephones	Telephone mainlines per thousand people	WDI
	Electricity	Kilowatt of electricity consumed per hour per capita	WDI
Human capital	Literacy rate	Percentage of people over 14 who can read and write a short, simple statement on their everyday life	WDI
	Mean years of schooling	Total number of years of school	BL**
	Secondary	Number of secondary years of school	BL
	Tertiary S&E enrolment ratio	Share of tertiary students in science and engineering	WDI
	Higher	Number of higher education years	BL
Other variables	Investment	Investment as a share of GDP	PWT***
	Trade	Exports of goods and services as a share of GDP	WDI
	Industry	Industry as a share of GDP	WDI
	Services	Services as a share of GDP	WDI
	GDP per capita	GDP per capita, PPPs, constant prices	PWT

*WDI: World Development Indicators, World Bank (2007)
** BL: Barro and Lee (2001)
***PWT: Penn World Tables, version 6.1

Appendix 2: The method of cluster analysis

The cluster analysis has been carried out in two subsequent phases. First, we have run a set of *hierarchical agglomerative* clustering algorithms (Gordon, 1999). In hierarchical agglomerative cluster analysis, all the cases are initially treated as individual clusters. Then, at each step, the most similar countries are merged together according to the overall 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. Since the results of cluster analysis are usually sensitive to changes in the clustering method used, we have run a large number of agglomerative algorithms, where we have used different methods (between groups linkage, within groups linkage, Ward's method) and different ways to measure the distance between cases (Euclidean, squared Euclidean, and cosine distance).

Secondly, after having identified the main clusters resulting from the hierarchical agglomerative methods, we have checked the robustness of the results by using a different clustering method, classification and regression tree analysis (CART). This is a flexible non-parametric method of cluster analysis (Breiman at al., 1984; Durlauf and Johnson, 1995). The general idea of CART is to construct a hierarchical classification of cases, where each step of the algorithm splits a group of cases into two sub-groups (*nodes*) based on one single predictor variable X_i. The CART algorithm follows three subsequent steps.

(1) The initial node (*root node*), which comprises all 149 countries in the sample, is split into two nodes, N_1 and N_2, on the basis of the predictor variable X_i that makes it possible to achieve the best split (searching among all possible splits, and both

predictor variables used as inputs in the analysis). The criterion to search for the best split is to reduce the node's *impurity measure*, i.e. to reduce the number of cases not belonging to a given category. A node is *pure* when all cases belonging to it refer to the same category.

(2) The same splitting rule is subsequently applied to all successive non-terminal nodes. A node is *terminal* when it is not possible to improve the misclassification rate by splitting it further into two subnodes. The resulting tree, T_{max}, tends to be large, because no cost for splitting has initially been specified. This means that splitting cases is costless, and that the tree will thus tend to have many branches and several terminal nodes.

(3) The tree T_{max}, therefore, does provide neither a correct idea of the right-sized tree, nor an accurate and honest estimate of its misclassification rate. For this reason, the tree must be *pruned*, i.e. the branches that are superfluous must be cut. This is achieved in two ways. First, the algorithm specifies costs associated to each successive split, so that the higher the number of splits, the greater the overall cost. Secondly, the CART selects the best pruned subtree among all possible pruned subtrees. This selection is obtained by using *v-fold cross-validation*, where the learning sample is partitioned into V equal parts, and the v_{th} fraction is used to evaluate the precision of the $(1\text{-}v)_{th}$ larger part. This leads to an estimation of the number of misclassified cases, so that the best pruned subtree is the one that minimizes the estimated misclassification rate.[11]

This clustering methodology, based on a combination of hierarchical agglomerative algorithms and CART analysis, differs from previous empirical studies (Durlauf and

[11] The v-fold cross-validation procedure also provides a useful device to calculate the statistical precision of the clustering exercise (Durlauf and Johnson, 1995). An alternative way has recently been investigated by Hansen (2000) and Los (2006), which have developed new methods to construct asymptotic confidence intervals for evaluating the existence of multiple regimes in the growth behaviour of a cross-section of countries.

Johnson, 1995; Johnson and Takeyama, 2001) in one important respect, since the search for the most efficient partition of the sample is not based on a regression model, and it therefore does not impose any *a priori* structure to the data. This strategy is therefore more line with the data-driven clustering methodology proposed by Desdoigts (1999).

Appendix 3: Composition of the three technology clubs

Cluster 1: *Advanced*

Australia, Austria[**], Belgium, Canada, Denmark, Finland, France, Germany, Iceland[**], Israel, Japan[**], Netherlands, New Zealand, Norway, Singapore[**], Sweden, Switzerland, UK, US

Cluster 2: *Followers*

Albania, Argentina, Armenia, Azerbaijan, Bahrain, Belarus, Bolivia, Botswana, Brazil, Bulgaria, Cameroon[***], Chile, China, Colombia, Republic of Congo, Costa Rica, Croatia, Cyprus, Czech Republic, Dominican Republic, Ecuador, El Salvador, Estonia, Fiji, Georgia, Ghana[***], Greece, Guyana, Honduras, Hong Kong, Hungary, Indonesia, Iran[***], Ireland, Italy, Jamaica, Jordan, Kazakhstan, Kenya, Korea, Kuwait, Kyrgyz. Republic, Latvia, Lebanon, Lesotho, Lithuania, Luxembourg, Macedonia, Malaysia, Malta, Mauritius, Mexico, Moldova, Namibia, Oman***, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Puerto Rico, Romania, Russia, Saudi Arabia, Slovak Republic, Slovenia, South Africa, Spain, Sri Lanka, Swaziland, Syria***, Tajikistan, Tanzania***, Thailand, Trinidad and Tobago, Tunisia***, Turkey, Turkmenistan, Uruguay, Ukraine, United Arab Emirates, Uzbekistan, Venezuela, Vietnam, Zambia, Zimbabwe

Cluster 3: *Marginalized*

Algeria, Angola, Bangladesh, Benin, Burkina Faso, Burundi, Cambodia, Central African Republic, Chad, Democratic Republic of Congo, Cote d'Ivoire, Djibouti, Egypt, Eritrea, Ethiopia, Gabon, Gambia, Guatemala, Guinea, Guinea-Bissau, Haiti, India, Lao, Madagascar, Malawi, Mali, Mauritania, Mongolia, Morocco, Mozambique, Nepal, Nicaragua, Niger, Nigeria, Pakistan, Papua New Guinea, Rwanda, Senegal, Sierra Leone, Sudan, Togo, Uganda, Yemen

** Countries belonging to the *followers* club in 1990

*** Countries belonging to the *marginalized* club in 1990

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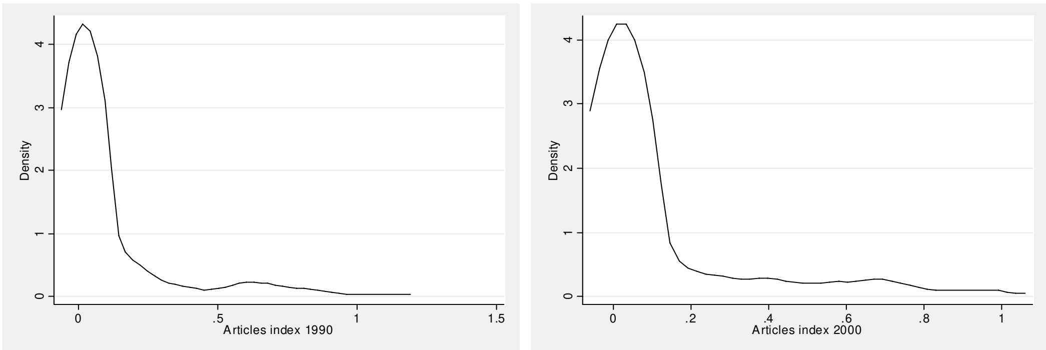
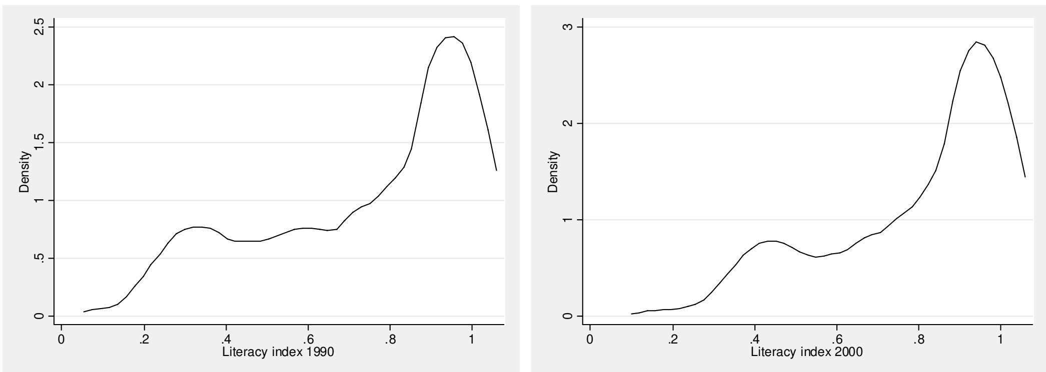
Tables and figures

Figure 1: Kernel density estimates of the two factors used as inputs in the cluster analysis: number of scientific articles per capita and literacy rate

Scientific articles, in 1990 (left) and 2000 (right)

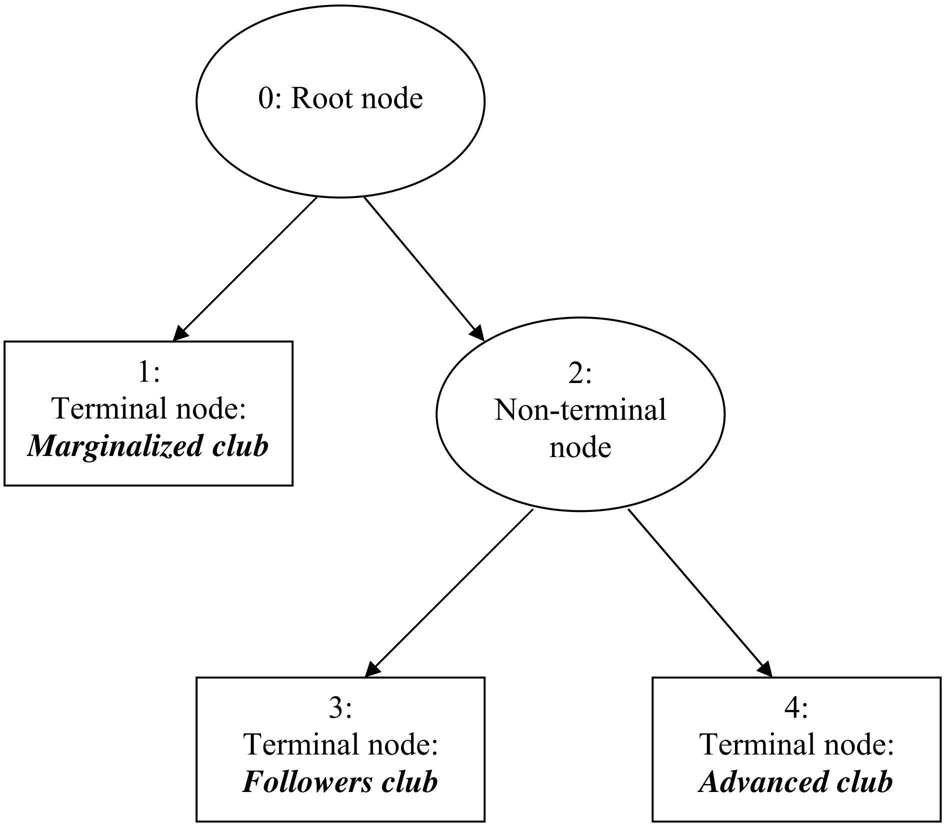


Literacy rate, in 1990 (left) and 2000 (right)



Notes: Epanechnikov kernel function; halfwidth of kernel: 0,06.
Both variables are in standardized form.

Figure 2: Results of the classification and regression tree (CART) analysis, 1990 and 2000



Year	Country club	Terminal node	Number of countries*	Splitting condition
1990**	Marginalized	1	50	Literacy rate < 66%
	Followers	3	84	Literacy rate > 66%; Articles < 340
	Advanced	4	15	Literacy rate > 66%; Articles > 340
2000**	Marginalized	1	43	Literacy rate < 70%
	Followers	3	87	Literacy rate > 70%; Articles < 346
	Advanced	4	19	Literacy rate > 70%; Articles > 346

Notes: * For a complete list of countries in each cluster, see Appendix 3.
** Cross-validation estimate of the regression tree results significant at 1% level.

Table 1: Technology clubs and technology gaps in the world economy in the 1990s

			Patents [a]	Scientific articles [a]	Internet users [b]	Computers [b]	Telephony [b]	Electricity consumption [c]	Tertiary S&E enrolment ratio	Mean years of schooling [d]	Literacy rate [d]	GDP per capita [e]	Population share
Technology clubs	**Club 1: Advanced**	**1990**	61,98	558,92	23,07	314,19	495,51	8476,75	10,41	9,38	98,20	18071	13,6%
		2000	88,14	620,75	265,41	492,70	1025,78	9621,47	17,53	9,96	98,49	25158	12,7%
	Club 2: Followers	**1990**	1,78	40,53	1,48	32,14	111,76	1868,04	5,10	5,88	85,70	6034	55,3%
		2000	2,84	52,12	37,86	57,97	289,74	2134,34	7,01	6,41	90,03	8327	54,1%
	Club 3: Marginalized	**1990**	0,01	3,29	0,01	3,86	6,66	138,32	0,86	2,29	39,32	1467	31,1%
		2000	0,01	3,31	1,32	7,53	17,93	162,42	1,22	2,62	49,85	1777	33,2%
Technology gaps [f]	**Advanced vs. Followers**	**1990**	34,75	13,79	15,58	9,77	4,43	4,54	2,04	1,59	1,15	2,99	-
		2000	31,01	11,91	7,01	8,50	3,54	4,51	2,50	1,55	1,09	3,02	-
	Followers vs. Marginalized	**1990**	222,98	12,32	282,18	8,33	16,78	13,50	5,96	2,57	2,18	4,11	-
		2000	224,01	15,76	28,79	7,69	16,16	13,14	5,75	2,44	1,81	4,69	-

Notes: [a] Per million people; [b] Per thousand people; [c] Kilowatt per hour per capita; [d] Population over 14; [e] PPPs; [f] The technology-gap is obtained by dividing the level of each indicator in the advanced (followers) club by the level of the same variable in the followers (marginalized) group.

Table 2: Econometric analysis of the Schumpeterian growth model:
Results of dynamic panel model estimation (Arellano-Bond GMM estimator[a]).

Base model specification

	Longer period: panel 1970-2000		Shorter period: panel 1985-2000	
	(1)	**(2)**	**(3)**	**(4)**
ΔInvestment	0.0627 (5.64)***	0.0743 (5.21)***	0.1468 (11.90)***	0.1281 (14.03)***
ΔTrade	-0.0004 (2.24)**	0.0001 (0.25)	-0.0004 (1.36)	0.0006 (2.24)**
ΔIndustry	0.0052 (2.28)**	-0.0006 (0.37)	0.0022 (0.96)	-0.0006 (0.35)
ΔServices	0.0026 (1.27)	0.0015 (0.83)	0.0017 (0.62)	-0.0023 (1.46)
ΔPatents	0.0014 (7.56)***	0.0017 (9.95)***	0.0010 (6.98)***	0.0010 (7.94)***
ΔArticles			0.1333 (11.80)***	0.0939 (11.45)***
ΔElectricity	0.1957 (7.32)***	0.1433 (3.21)***	0.2496 (9.71)***	0.1373 (6.52)***
ΔTelephony	0.0146 (2.77)***	0.0050 (1.32)	0.0182 (3.28)***	0.0063 (1.31)
ΔComputer			0.0131 (4.91)***	0.010 (3.93)***
ΔInternet			-0.0032 (1.60)	-0.0082 (6.26)***
ΔSecondary	-0.0377 (1.43)	-0.0345 (1.16)	-0.1303 (6.32)***	-0.1097 (9.83)***
ΔHigher	-0.0739 (3.41)***	-0.2249 (5.04)***	0.0106 (0.47)	-0.1067 (5.11)***
Δ(GAP•Higher)		0.1003 (4.89)***		0.1579 (8.86)***
ΔGDPPC	0.5061 (20.83)***	0.4826 (23.70)***	0.1719 (7.08)***	0.1754 (8.34)***
Constant	0.0214 (3.09)***	0.0381 (3.25)***	0.0353 (4.03)***	0.0747 (9.83)***
Time dummies	Yes	Yes	Yes	Yes
Sargan test	60.82	57.17	49.85	48.10
Autocorrelation (1)	-4.06***	-3.66***	-0.20	-0.91
Autocorrelation (2)	-0.27	0.08	-0.76	-1.39
Wald χ^2	2051.8	5096.6	85553.2	33845.8
Countries	69	69	66	66
Observations	329	329	136	136

[a] Arellano and Bond GMM two-step estimator
*** Significance at 1% level; ** Significance at 5% level; * Significance at 10% level

Table 3: Econometric analysis of the Schumpeterian growth model:
Results of dynamic panel model estimation (Arellano-Bond GMM estimator[a]).

Piecewise linear model specification (slopes differing across the country clubs)

		Longer period: panel 1970-2000		Shorter period: panel 1985-2000	
	Country club[b]	**(5)**	**(6)**	**(7)**	**(8)**
ΔInvestment	A	0.4190 (2.83)***	0.2479 (2.07)**	0.3069 (2.22)**	0.1538 (1.57)
	F	0.0658 (1.98)**	0.0282 (1.14)	0.0619 (1.84)*	0.0169 (0.70)
	M	-0.0207 (0,28)	-0.0493 (0.87)	0.1620 (1.35)	0.1055 (1.21)
ΔTrade	A	0.0001 (0.08)	0.0008 (0.57)	-0.0012 (0.66)	0.0003 (0.21)
	F	0.0018 (2.24)**	0.0024 (3.73)***	0.0018 (1.82)*	0.0016 (2.26)**
	M	-0.0016 (0.72)	-0.0024 (1.38)	-0.0089 (3.02)***	-0.0054 (2.39)**
ΔIndustry	A	-0.0019 (0.08)	-0.0016 (0.09)	-0.0037 (0.18)	0.0062 (0.44)
	F	0.0091 (2.91)***	-0.0004 (0.18)	0.0012 (0.33)	-0.0066 (2.50)**
	M	0.0203 (2.82)***	0.0032 (0.55)	0.0189 (1.97)**	0.0128 (1.84)*
ΔServices	A	-0.0085 (0.37)	-0.0035 (0.21)	-0.0114 (0.57)	-0.0002 (0.01)
	F	0.0040 (1.26)	0.0025 (1.11)	-0.0084 (2.09)**	-0.0055 (1.96)**
	M	0.0164 (3.10)***	-0.0044 (0.85)	0.0174 (1.87)*	0.0072 (1.02)
ΔPatents	A	0.0009 (1.26)	0.0008 (1.48)	0.0006 (1.05)	0.0003 (0.60)
	F	0.0052 (2.57)***	0.0089 (5.89)***	0.0058 (2.99)***	0.0074 (5.53)***
	M	0.107 (0.59)	0.0263 (0.19)	-0.1349 (0.57)	-0.2458 (1.44)
ΔArticles	A			0.0274 (1.20)	0.0257 (1.57)
	F			0.0955 (2.89)***	0.0946 (4.02)***
	M			0.1728 (2.46)**	0.2123 (4.15)***
ΔElectricity	A	0.1562 (0.92)	0.1287 (1.02)	0.1284 (0.90)	0.1083 (1.13)
	F	0.0234 (0.86)	0.0471 (2.22)**	0.0051 (0.18)	0.0424 (2.08)**
	M	0.0321 (0.89)	0.0247 (0.87)	0.0203 (0.48)	0.0302 (0.97)
ΔTelephony	A	-0.0030 (0.21)	0.0025 (0.22)	-0.0390 (0.67)	-0.0168 (0.41)
	F	0.0172 (0.99)	0.0092 (0.71)	0.0333 (1.58)	0.0256 (1.74)*
	M	0.0239 (0.73)	0.0703 (2.71)***	0.0037 (0.04)	0.0607 (0.98)

ΔComputer	A			0.1444 (2.53)**	0.1368 (3.37)***
	F			0.0119 (1.16)	0.0045 (0.62)
	M			0.0522 (0.99)	0.0074 (0.19)
ΔInternet	A			-0.0081 (0.61)	-0.0152 (1.59)
	F			0.0165 (1.58)	0.0071 (0.96)
	M			0.0052 (0.40)	0.0067 (0.73)
ΔSecondary	A	0.1236 (0.83)	0.1264 (1.13)	0.1266 (1.16)	0.0643 (0.83)
	F	0.1222 (2.70)***	0.0986 (2.86)***	0.1494 (3.11)***	0.1130 (3.34)***
	M	0.0294 (0.45)	0.0779 (1.53)	-0.077 (0.82)	-0.0855 (1.26)
ΔHigher	A	0.1274 (1.80)*	-0.0358 (0.33)	0.1636 (2.45)**	-0.1312 (1.47)
	F	-0.0477 (1.69)*	-0.2410 (8.40)***	-0.033 (1.13)	-0.3004 (9.29)***
	M	-0.0472 (1.06)	-0.3931 (6.37)***	0.0469 (0.80)	-0.4023 (3.91)***
Δ(GAP•Higher)	A		0.4702 (1.92)*		0.7393 (3.55)***
	F		0.1237 (8.82)***		0.1808 (10.34)***
	M		0.1715 (6.32)***		0.1953 (4.80)***
ΔGDPPC		0.4661 (7.15)***	0.2355 (4.89)***	0.1762 (2.11)**	0.1187 (2.07)**
Constant		-0.1412 (1.00)	0.0020 (0.11)	-0.0299 (0.22)	-0.2004 (2.04)**
Time dummies		Yes	Yes	Yes	Yes
Sargan test		162.13	185.11	145.79	152.36
Autocorrelation (1)		-5.03***	-3.14***	-2.77***	-1.53
Autocorrelation (2)		-0.70	-0.50	0.12	-1.03
Wald χ^2		279.2	614.5	244.8	645.9
Countries		69	69	68	68
Observations		353	353	256	256

[a] Arellano and Bond GMM one-step estimator

[b] Country clubs – A: Advanced; F: Followers; M: Marginalized

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