Industrial and Corporate Change, Volume 20, Number 2, pp. 457–510
doi:10.1093/icc/dtr003

Does structure influence growth? A panel data econometric assessment of "relatively less developed" countries, 1979–2003

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Neo-Schumpeterian streams of research emphasize the close relationship between changes in economic structure in favor of high-skill and high-tech branches and rapid economic growth. They identify the emergence of a new technological paradigm in the 1970s, strongly based on the application of information and communication technologies (ICTs), arguing that in such periods of transition and emergence of new techno-economic paradigms, the intermediate development countries and the countries which are not at the technological frontier have higher opportunities to catch-up. Although this debate is theoretically well documented, the empirics seem to lag behind the theory. In this article, we contribute to this literature by adding enlightening evidence on the issue. More precisely, we relate the growth experiences of countries which had relatively similar economic structures in the late 1970s, with changes occurring in these countries' structures between 1979 and 2003. The results reveal a robust relationship between structure and (labor) productivity growth, and lend support to the view that *producing* (though not user) ICT-related industries are strategic branches of economic activity.

JEL classification: O10, O30.

1. Introduction

Structural change refers primarily to changes in the sectoral composition of the economy (Silva and Teixeira, 2008; Wang and Szirmai, 2008), and may be driven

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either by demand-side factors, such as changes in domestic demand and in the structure of exports, or by supply-side factors, such as the re-allocation of labor and capital to more efficient uses.

The last two decades witnessed a revival of interest in structural change and in its relationship with economic growth, which seems to be primarily related with the spread of neo-Schumpeterian concepts (Silva and Teixeira, 2008). According to the arguments put forward in this branch of economic literature [see especially, Perez (1985) and Freeman and Perez (1988)], major technological breakthroughs have a profound impact on the restructuring of the techno-economic and socio-institutional spheres of the economy. With respect to the sectoral composition of the economy, the introduction of a new "technological paradigm" (Dosi, 1982) leads to significant changes, where a dynamic set of industries that is more closely related with its exploitation assumes progressively greater importance and stimulates growth, whereas sectors associated with older technologies see their influence decline. Along with these important developments, some theoretical models within the more orthodox branch of economics also came into play, suggesting that countries specializing in high-tech sectors could achieve high rates of productivity growth relative to other countries (Grossman and Helpman, 1991; Lucas, 1993). Lucas (1988) even suggested that it could pay off for a country to change its specialization pattern from low- to high-tech sectors by adopting adequate policy measures.

The emphasis put by these theoretical approaches on the relationship between technologically advanced industries and economic growth, together with the debate on the impact of information and communication technologies (ICT) on aggregate productivity growth, gave rise to a number of empirical studies examining the impact of structural change on economic growth (e.g. Fagerberg, 2000; Timmer and Szirmai, 2000; Meliciani, 2002; Peneder, 2003; Castellaci, 2007; Wang and Szirmai, 2008). Some of these studies consider a relatively large group of countries, grouping countries with marked structural differences (e.g. Amable, 2000; Fagerberg, 2000; Meliciani, 2002; Peneder, 2003; Castellaci, 2007), whereas others focus on experiences in individual countries or regions (e.g. Hobday, 1995; Nelson and Pack, 1999; Timmer and Szirmai, 2000; Engelbrecht and Xayavong, 2007; Wang and Szirmai, 2008). To our knowledge, however, an attempt has yet to be made to assess the role of technology-led branches taking specifically into account the countries which were relatively less developed at the emergence of the new ICT paradigm, and could therefore benefit more from adopting new technologies (Perez, 1985). This is the main focus of this study. Our purpose is not so much to assess globally the impact of technology-led sectors on economic growth, an issue that has already been addressed in the literature (e.g. Fagerberg, 2000; Meliciani, 2002; Peneder, 2003), but to investigate their specific importance with respect to countries which were not at the technological frontier in the late 1970s, and shared similar structural characteristics in that time period.

The period under analysis (1979–2003) was characterized by the emergence of a new techno-economic paradigm, strongly based on the application of ICT (Freeman and Soete, 1997), which replaced the previous paradigm based on low-cost oil and mass-production technologies. According to some views expressed within the new Schumpeterian approach (e.g. Perez, 1985), it is precisely in periods of transition and emergence of new techno-economic paradigms that the relatively less developed countries have greater opportunities to catch-up. In these circumstances, it seems pertinent to compare economies that faced similar growth problems in the late 1970s and which have experienced widely different growth trajectories since then, and relate those experiences with changes occurring at the industry level of the economy. This is accomplished in the present work by exploring the causality links between industry and macro-level changes, taking into account a set of 10 "relatively less developed" countries in the late 1970s, namely, Austria, Finland, Greece, Ireland, Italy, Japan, South Korea, Portugal, Spain, and Taiwan. Despite presenting some differences in per capita income and education levels, these countries share economic structures that strongly rely on low-skill and low-tech industries, which indicate their relative backwardness in technological terms.

The analysis of the trajectories of a restricted set of relatively homogeneous countries during the 1979–2003 span is further justified on empirical and theoretical grounds by the consideration that countries follow very different growth patterns. Given the strong empirical rejection of the hypothesis of a common growth model for all countries in favor of the idea of different convergence clubs (e.g. Durlauf and Jonhson, 1992; Färe *et al.*, 2006), it does indeed seem more reasonable to analyze separately a group of economies that shared similar structural characteristics at the beginning of the period under study.

In comparison with previous studies on the relationship between growth and structural change, this analysis also provides a more comprehensive approach, by taking into account both the impact of manufacturing and services technologically-leading sectors in the growth performance of countries. Evidence found in recent studies (e.g. Inklaar *et al.*, 2008; van Ark *et al.*, 2008) points to an important role played by some service subsectors, and particularly those more closely related to ICT technologies, as sources of aggregate productivity growth. This assumption is investigated in this study with respect to the set of 10 relatively less developed countries in the late 1970s.

The article is structured as follows. Section 2 provides a brief discussion of the theoretical groundings of the analysis between growth and structural change and clarifies the main theoretical arguments that sustain the empirical exercise undertaken. Section 3 identifies the list of countries to be compared by applying hierarchical cluster analysis. Section 4 provides a descriptive characterization of the growth and structural change processes of the selected countries during the period considered. It is shown that a striking increase in the countries' dissimilarities came into play during this period, and an association between changes in economic performance and changes in economic structure is hypothesized. In Section 5, this possibility is examined through the estimation of dynamic panel data regressions. The results reveal a robust relationship between structure and labor productivity growth, although the impact of ICT industries is only relevant when ICT producing manufacturing industries are considered. The final section presents a brief summary and concludes.

2. Productivity growth and structural change: theoretical considerations

The marked upsurge of empirical research on structural change in the last few decades can be related with a greater concern by the part of economists with the study of technological change and innovation, to which the emergence of the *New Economy* and the controversy generated around the "productivity paradox" have contributed greatly (Silva and Teixeira, 2008). A prolific strand of applied work focusing on the impact of leading technological sectors, and in particular of IT-related industries, has thus emerged, using a vast assortment of empirical methods (e.g. Robinson *et al.*, 2003; Franke and Kalmbach, 2005; van Ark *et al.*, 2008; Mahony and Vechi, 2009).

The intense proliferation of empirical research in the field has not, however, been accompanied by a clarification of the corresponding theoretical groundings. Indeed, a substantial amount of studies in this area does not provide any indication whatsoever as to the fundamentals of the research undertaken, whereas in other cases the references given are so broad, encompassing concurrent views on the study of technology and innovation, such as evolutionary and neoclassical views, that they barely offer satisfactory guidance to the empirical analysis.

With respect to the applied work of structural change, mainstream economic theory does not seem to provide sound theoretical underpinnings. The prevailing theory of economic growth has been able to produce totally aggregate growth models, generally based on neo-classical production functions, and multi-sectoral models in which structure remains unchanged through time, but not models which represent the changing structure of the economy that inevitably accompanies growth. The analytical treatment of economic growth has been carried out more in a way to avoid analytical complications, than as a means to get as close as possible of the concrete facts of reality. In this context, descriptive realism and historical evidence have been sacrificed to the requirements of formal mathematization, and qualitative changes, such as changes in the composition of the economic system, have been omitted in the modeling framework. At the same time, mainstream economic theory has been developed considering equilibrium analysis and optimization assumptions, which by definition rule out any examination of problems related with the disruption and restructuring of the productive structure. The dynamics of this type of models, dictated by the choice of the relevant conditions—such as preference parameters—allows for a comparative analysis of different steady growth paths but does not permit the analysis of out-of-equilibrium situations (Amendola and Gaffard, 1998). Therefore, although some structural change features can be taken into account, such as a change in technique or an increase in the variety of consumer goods, the notion of growth as a *process* is irremediably lost: "equilibrium models are aimed at identifying growth factors and measuring their respective contribution to growth, so as to be able to derive policy implications", but "there is no attempt to understand the *working of the growth mechanism*, which is assumed in the model" (Amendola and Gaffard, 1998: 115, emphasis added).

In this context, the theoretical bases of applied work on structural change have to be found elsewhere in the literature. Pasinetti's work on structural dynamics has been identified as one of the most rigorous formulations to date of a structural model of economic growth (Silva and Teixeira, 2008). The point of departure of the model consists precisely in assuming that technical progress and demand changes (the main engines of growth) have an uneven impact across sectors. Uneven technical progress allows for an increase in productivity that is translated into growing uncommitted income; higher levels of disposable income generate, in turn, a change in demand patterns (through Engel's law), with the consequent changes in the composition of the economy and in the path of sustained growth. The model thus establishes a link between technological advances, growth and structural change, in such a way as to be useful to the empirical research on the matter. Nevertheless, for this study, Pasinetti's theoretical scheme does not offer more than general guidance. Indeed, the model is centred on achieving a single purpose—to define the conditions under which it is possible to obtain approximate full employment of resources in an environment of continuous technical change—which although exploring some of the links approached in our work, namely the connection between the emergence of new industries and economic growth, it does so in a lateral manner. As Gualerzi (2001: 27) highlights, although "new industries and new products can be represented in the model", they "do not become forces of change and the model does not acquire dynamism from them", which rules out any strict application of Pasinetti's theoretical framework in the present work.

In order to obtain a more appropriate theoretical background for the applied work undertaken we turn to an alternative, yet complementary, approach to the study of the process of economic growth and structural change: the neo-Schumpeterian framework.[1] Neo-Schumpeterian theory elaborates on the original contribution of Schumpeter relating innovation with renewed economic growth and "creative destruction". Schumpeter saw economic development as endogenously determined by innovation and entrepreneurial investment. Economic fluctuations, and most particularly, Kondratieff waves of half a century, were

[1]See Fagerberg (2003) for an extended discussion on the emergence and consolidation of the neo-Schumpeterian stream of research.

explained on the basis of the discontinuous introduction of swarms of basic innovations and its subsequent diffusion in a bandwagon pattern throughout the economy. Although these ideas were received with great scepticism at the time of their publication (e.g. Kuznets, 1940), in the recession period of the 1970s and 1980s the role of basic innovations in generating "long waves" of growth gained new interest, with a number of new-Schumpeterian economists addressing the issue, and giving rise to what is currently known as the "long-wave" literature (e.g. Mensch, 1979; Clark *et al.*, 1981; Kleinknecht, 1986, 1990; Freeman and Perez, 1988).

This study takes into account the theoretical insights developed by the neo-Schumpeterian literature, namely its emphasis on the profound impact of the diffusion of major technological breakthroughs on the structure of the economy and on economic growth, without adhering to the idea of a strict periodicity of "long-waves". We are particularly interested in exploring the joint impact of structural change and technological progress on the evolution of countries' productivity in the 1979–2003 period, focusing on the role played by technologically leading sectors. According to the neo-Schumpeterian literature, the technological revolution underlying this period is based on ICT, which would drive a new upswing of economic growth starting in the 1980s or 1990s (see Freeman *et al.*, 1982; Freeman and Soete, 1997). This new "information age", based on the exploration of cheap microelectronics (Perez, 1985), followed the older paradigm based on mass production technologies and low-cost oil, which had its golden period in the 1950s and 1960s.

Following the arguments expressed in the literature (Perez, 1985; Freeman and Perez, 1988), the emergence of a major technological breakthrough has a profound impact on the restructuring of the techno-economic and socio-institutional spheres of the economy. With respect to the sectoral composition of the economy, the introduction of a new technological paradigm originates significant changes, where a dynamic set of industries that is more closely related with its exploitation assumes progressively greater importance and stimulates growth, whereas sectors associated with older technologies see their relative influence decline.

Along with changes in the growth rates and the productive structure of the economy, there is also important institutional and social change. As argued in the neo-Schumpeterian theory, diffusion is never immediate or automatic, but is strongly dependent on a number of characteristics of the "receiving" economy, and in particular on the ability to adapt its institutions to new forms of organization and management of the economic activity required by the new technological paradigm (Perez, 1985; Freeman and Perez, 1988).

Successful catch-up, it is argued, can only be achieved by countries that possess adequate "social capabilities", that is, those with sufficient educational attainments and adequately qualified and organized institutions that enable them to exploit the available technological opportunities (Fagerberg, 1994). The pace at which the potential for catch-up is realized depends furthermore on a number of factors, related with the ways in which the diffusion of knowledge is made, the domestic capability to innovate, the pace of structural change, the rates of investment and expansion of demand, and the degree of "technological congruence" (Abramovitz, 1986, 1994) of the backward country in relation to the technological leader. With respect to the new technological paradigm (the ICT revolution), the requirements imposed in terms of skills (investment in human capital) and infrastructure (investment in physical capital) seem to be particularly high, making catching up on the basis of diffusion more difficult (Fagerberg and Verspagen, 2002).

Based on the neo-Schumpeterian literature and its emphasis on the relationship between technology, structural change and economic growth, we analyze the growth performance of a number of countries in terms of the observed changes in economic structure towards skill and technology-intensive industries. The analysis of causality links between changes in structure and economic growth takes into account the countries' investments in both human and physical capital, which are prior requirements to the adoption and creation of technology (cf. Section 5).

3. Determining the countries' structural similarity: a cluster analysis

3.1 Variables and data sources

In order to identify the group of relatively less developed countries which shared similar structural characteristics in the late 1970s, a comparison of 21 countries (20 OECD members plus Taiwan) is undertaken.[2]

The assessment of similarity among countries is based on three major features: per capita income, educational attainment of the workforce, and the composition of economic activity. Per capita income is still an important measure used in the assessment of countries' economic and social development differences, despite its well-known deficiencies (cf. Khan, 1991). Data on this variable are taken from the *World Economic Outlook Database* (April 2008) of the International Monetary Fund.[3]

Along with per capita income, a measure of human capital stock is included, expressed by the average number of years of formal education of the working age population (25–64 years). The choice of this variable reflects the crucial role of

[2]Although a larger set of countries would increase the discriminatory power of the cluster analysis, more countries could not be included due to data limitations. In particular, data at the industry-level comprising both manufacturing and services at a reasonably large disaggregation level and covering the entire 1979–2003 span are only available for the list of countries effectively considered. This list can be found in Table 1.

[3]This database provides full information regarding per capita GDP based on purchasing-power-parity (PPP) in current international dollars for a vast number of countries for the 1980–2007 period.

education in determining the capacity to assimilate advanced technologies from more developed countries, and to foster rapid structural change and economic growth (cf. Section 2). Most of the data regarding this variable are taken from Bassanini and Scarpetta (2001). The authors extend de la Fuente and Doménech's (2000) earlier computations, determining the average number of years of formal education of the working age population on an annual basis over the 1971–1998 period.[4] We consider additionally Barro and Lee's (2001) estimates for the same variable for Korea and Taiwan, because these countries were not taken into account in Bassanini and Scarpetta's work.[5]

With regard to the composition of economic activity, three complementary industry taxonomies are considered: a slightly modified version of the taxonomy proposed by Tidd *et al.* (2005), based on innovation and technological characteristics of industries; a taxonomy from Peneder (2007), which classifies industries according to their skill requirements; and finally, an ICT-based taxonomy from Robinson *et al.* (2003), which ranks industries according to their production or use of ICT.

The innovation taxonomy suggested by Tidd *et al.* (2005) constitutes a refinement of Pavitt's original classification scheme (Pavitt, 1984) which includes the information-intensive category along with the former Pavitt categories: supplier-dominated, scale-intensive, science-based, and specialized suppliers. These four categories establish a gradual scale of technological opportunities, identified with the number of significant innovations achieved: they are lowest in supplier-dominated firms, in which most of the technological advances come from suppliers of equipment and other inputs; they are relatively higher in scale-intensive firms, which develop investment and production activities in large-scale production systems and major sources of innovation come from production engineering departments and suppliers of specialized inputs; and finally, they are highest in science-based and in specialized supplier firms, the former characterized by high levels of in-house R&D and strong links with science, and the latter facing continuous pressures to improve efficiency on the part of their users. In later work (e.g., Pavitt, 1990; Tidd *et al.*, 2005), the information-intensive category is included to take into account the firms/industries that benefit most from the new technological breakthrough, such as financial and

[4]Up to the early 1980s, Bassanini and Scarpetta (2001) interpolate the 5-year estimates provided by de la Fuente and Doménech (2000), whereas from that date onwards they calculate average years of education based on data from the OECD *Education at a Glance* (various issues), and consider the cumulative years of schooling in each educational level described in the OECD (1998: 347).

[5]Barro and Lee (2001) show that the estimates of educational attainment based on OECD data are quite similar to their own measures, and therefore the inclusion of a different source of information does not seem to be problematic. The major differences arise with respect to Germany and the UK, because of a different classification of educational attainment between the OECD and the UNESCO sources.

retail services.[6] We use a slightly modified version of this latter taxonomy, considering additionally the non-market services category (cf. Table 1), in a way similar to Robinson *et al.* (2003). The inclusion of non-market services is intended to take into account the specificities of non-profit activities, such as public administration, education, and health. Generally, nonprofit activities obey a distinct logic in terms of the relationship between innovation and productivity growth (Lumpkin and Dess, 1996; McDonald, 2007), and therefore it seemed reasonable to include them in a separate category.[7]

The second taxonomy, from Peneder (2007), classifies industries according to their educational workforce composition, distinguishing among seven categories, from very high to very low educational requirements (cf. Table 1).[8] It combines educational attainment data, compiled in a collective effort coordinated by the National Institute of Economic and Social Research (NIESR), with industry data gathered from the OECD STAN database. The "very low" educational intensity category includes only supplier-dominated industries, such as agriculture and textiles, whereas the "very high" category encompasses sectors such as education, research and development, and computer and related activities. The "medium" and "medium high" categories represent the largest groups, including, among others, "science-based" industries (chemicals and radio and television receivers as "medium high" and other electrical machinery as "medium"), and specialized suppliers (telecommunication equipment and scientific instruments as "medium high" and mechanical engineering and insulated wire as "medium").

Finally, the ICT taxonomy is based on the original classification of OECD (2002) which distinguished between ICT producing and using industries. Considering additionally non-ICT industries, Robinson *et al.* (2003) propose a seven group taxonomy

[6]A new taxonomy built upon innovation studies literature and sharing some commonalities with that of Tidd *et al.* (2005) has been recently presented by Castellacci (2008). Combining manufacturing and services industries within the same framework, this taxonomy highlights the role played by vertical linkages and inter-sectoral knowledge exchanges between those industries. More specifically, it proposes four major categories: (i) advanced knowledge providers (knowledge intensive business services, specialized suppliers manufacturing), (ii) supporting infrastructural services (network infrastructure, physical infrastructure), (iii) mass-production goods (science-based manufacturing, scale-intensive manufacturing), and (iv) personal goods and services (supplier dominated goods, supplier dominated services).

[7]Tidd *et al.* (2005) provide examples of industries included under each of the taxonomical categories, but of course they do not cover the entire set of industries considered in the present work. Our classification is based on our own interpretation of the authors' taxonomy, and on previous applied work using Pavitt-type taxonomies (e.g. Robinson *et al.*, 2003).

[8]Robinson *et al.* (2003) present an alternative skill taxonomy, based on the Eurostat Labor Force Survey data, which is devised in a way similar to Peneder's. Although there are some differences in the classification of industries in the intermediate categories (Peneder's taxonomy is more disaggregated), the two taxonomies present many similarities in terms of the classification of the 56 industries considered in this research.

Table 1 Classification of sectors according to the selected taxonomies

ISIC revision 3	Industries	Peneder (2007)	Tidd *et al.* (2005)	Robinson *et al.* (2003)
01	Agriculture	Very low	Supplier-dominated	Non-ICT Other
02	Forestry	Very low	Supplier-dominated	Non-ICT Other
05	Fishing	Very low	Supplier-dominated	Non-ICT Other
10–14	Mining and quarrying	Medium	Scale-intensive	Non-ICT Other
15–16	Food, drink, and tobacco	Low	Scale-intensive	Non-ICT manufacturing
17	Textiles	Very low	Supplier-dominated	Non-ICT manufacturing
18	Clothing	Very low	Supplier-dominated	ICT using manufacturing
19	Leather and footwear	Very low	Supplier-dominated	Non-ICT manufacturing
20	Wood and products of wood, and cork	Very low	Supplier-dominated	Non-ICT manufacturing
21	Pulp, paper, and paper products	Medium	Supplier-dominated	Non-ICT manufacturing
22	Printing and publishing	Medium	Supplier-dominated	ICT Using manufacturing
23	Mineral oil refining, coke, and nuclear fuel	Medium	Scale-intensive	Non-ICT manufacturing
24	Chemicals	Medium-high	Science-based	Non-ICT manufacturing
25	Rubber and plastics	Medium-low	Specialized supplier	Non-ICT manufacturing
26	Non-metallic mineral products	Low	Scale-intensive	Non-ICT manufacturing
27	Basic metals	Low	Scale-intensive	Non-ICT manufacturing
28	Fabricated metal products	Low	Scale-intensive	Non-ICT manufacturing
29	Mechanical engineering	Medium	Specialized supplier	ICT using manufacturing
30	Office machinery	High	Specialized supplier	ICT producing manufacturing
313	Insulated wire	Medium	Specialized supplier	ICT producing manufacturing
31–313	Other electrical machinery and apparatus nec	Medium	Science-based	ICT using manufacturing
321	Electronic valves and tubes	Medium-high	Specialized supplier	ICT producing manufacturing
322	Telecommunication equipment	Medium-high	Specialized supplier	ICT producing manufacturing
323	Radio and television receivers	Medium-high	Science-based	ICT producing manufacturing

(continued)

Table 1 Continued

ISIC revision 3	Industries	Peneder (2007)	Tidd *et al*. (2005)	Robinson *et al*. (2003)
331	Scientific instruments	Medium-high	Specialized supplier	ICT producing manufacturing
33–331	Other instruments	Medium-high	Specialized supplier	ICT using manufacturing
34	Motor vehicles	Medium	Scale-intensive	Non-ICT manufacturing
351	Building and repairing of ships and boats	Medium-high	Scale-intensive	ICT using manufacturing
353	Aircraft and spacecraft	Medium-high	Scale-intensive	ICT using manufacturing
352+359	Railroad equipment and transport equipment nec	Medium-high	Scale-intensive	ICT using manufacturing
36–37	Furniture, miscellaneous manufacturing; recycling	Medium-low	Supplier-dominated	ICT using manufacturing
40–41	Electricity, gas and water supply	Medium	Scale-intensive	Non-ICT other
45	Construction	Low	Supplier-dominated	Non-ICT other
50	Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of automotive fuel	Low	Information-intensive	Non-ICT services
51	Wholesale trade and commission trade, except of motor vehicles and motorcycles	Medium	Information-intensive	ICT using services
52	Retail trade, except of motor vehicles and motorcycles; repair of personal and household goods	Medium-low	Information-intensive	ICT using services
55	Hotels and catering	Very low	Supplier-dominated	Non-ICT services
60	Inland transport	Medium-low	Information-intensive	Non-ICT services
61	Water transport	Medium-low	Information-intensive	Non-ICT services
62	Air transport	Medium-high	Information-intensive	Non-ICT services
63	Supporting and auxiliary transport activities; activities of travel agencies	Medium	Supplier-dominated	Non-ICT services
64	Communications	Medium	Information-intensive	ICT producing services
65	Financial intermediation, except insurance and pension funding	High	Information-intensive	ICT using services

(continued)

Table 1 Continued

ISIC revision 3	Industries	Peneder (2007)	Tidd *et al.* (2005)	Robinson *et al.* (2003)
66	Insurance and pension funding, except compulsory social security	Medium-high	Information-intensive	ICT using services
67	Activities auxiliary to financial intermediation	Medium-high	Information-intensive	ICT using services
70	Real estate activities	Medium	Information-intensive	Non-ICT services
71	Renting of machinery and equipment	Medium	Information-intensive	ICT using services
72	Computer and related activities	Very high	Specialized supplier	ICT producing services
73	Research and development	Very high	Specialized supplier	ICT using services
741–3	Legal, technical, and advertising	High	Specialized supplier	ICT using services
749	Other business activities, nec	High	Information-intensive	Non-ICT services
75	Public administration and defence; compulsory social security	Medium-high	Non-market services	Non-ICT services
80	Education	Very high	Non-market services	Non-ICT services
85	Health and social work	Medium-high	Non-market services	Non-ICT services
90–93	Other community, social and personal services	Medium-high	Supplier-dominated	Non-ICT services
95	Private households with employed persons	Very low	Supplier-dominated	Non-ICT services
99	Extra-territorial organizations and bodies	Very high	Non-market services	Non-ICT services

which ranks industries according to their production or use of ICT: ICT producing manufacturing (ICTPM), ICT producing services (ICTPS), ICT using manufacturing (ICTUM), ICT using services (ICTUS), Non-ICT manufacturing (NICTM), Non-ICT services (NICTS) and non-ICT other industries (NICTO). The former two categories, ICTPM and ICTPS, include industries that directly produce ICT goods and services, namely telecommunication equipment, radio and television receivers, scientific instruments, communications and computer related activities (cf. Table 1). In general, ICTPM industries include specialized suppliers industries characterized by high or medium-high educational intensity, whereas supplier-dominated industries are mostly represented within the non-ICT category, and are characterized by low or very low educational intensity levels.

The relative shares of the countries' industries are computed according to the three classification schemes, taking into account both gross value added and employment figures. Data on sectoral value added in current prices and employment (in hours) are taken from the 60-Industry Database of the Groningen Growth and Development Center, which is available on-line at: http://www.ggdc.net. This database covers 26 countries for 56 industries classified according to the International Standard Industrial Classification (ISIC) revision 3. Table 1 presents the classification of the 56 industries according to the selected taxonomies.[9]

3.2 Countries' characterization in the late 1970s

Table 2 presents the list of variables considered in the cluster analysis for our sample of 21 countries.[10]

As can be seen in Table 2, countries with larger per capita incomes tend to have higher educational capital stocks and relatively higher shares of high-skill industries. Inversely, countries with relatively low levels of GDP per capita income and human capital have higher shares of low-skill and supplier-dominated industries, the industry group with fewer technological opportunities. The US and Germany, for example,

[9]The use of the three distinct taxonomies facilitates considerably the analysis of the impact of technological and educational characteristics on the growth performance of countries, but it should be noted that they have some limitations of their own. For instance, we can find "supplier-dominated" firms in radio and TV receivers, electronics and chemicals, and "science-based" firms in agriculture, despite, as Tidd *et al.* (2005: 174) point out "they are unlikely to be technological pacesetters". Moreover, given the fact that the selected taxonomies are based on developed countries' industrial frames, it is likely that for less-developed countries they might not be as robust as desired. More precisely, some industries, such as radio and TV receivers, considered as "science-based" when the reference country is a developed country, might, in the case of a developing country, include mainly assembling firms with few technological and educational requirements [cf. Hobday (1995)].

[10]Table A1 in the Appendix A provides information on the industry groups considering the employment data.

Table 2 Industry shares in total gross value added (%), average number of years of formal education of the working age population and per capita income (1979, various countries)

	Skill categories			Innovation categories						ICT categories							Education	PPPpcGDP[c]
	Aggregate low[a]	Medium	Aggregate high[b]	Supplier-dominated	Scale-intensive	Specialized supplier	Science-based	Information-intensive	Non-market services	ICTPM	ICTPS	ICTUM	ICTUS	NICTM	NICTS	NICTO	Years	Current international dollar
Australia	37.1	32.2	30.7	25.1	19.7	5.6	1.8	31.1	16.7	0.6	2.4	4.9	14.1	13.9	39.3	24.7	11.5	9809.80
Austria	44.5	25.0	30.6	28.2	14.8	6.1	2.4	31.9	16.6	1.4	2.4	6.2	19.8	16.3	36.1	17.9	10.3	10,495.00
Belgium	33.0	24.6	42.4	18.4	17.1	11.0	4.2	29.4	19.9	1.1	4.0	5.1	24.9	16.9	32.7	15.3	9.2	9758.30
Canada	34.0	34.3	31.8	22.8	18.7	5.5	1.9	32.6	18.5	1.1	2.8	4.7	14.9	13.8	41.2	21.5	12	11,119.80
Denmark	34.3	28.9	36.8	21.2	9.7	7.1	1.7	37.9	22.3	0.9	2.0	6.7	21.5	10.4	45.7	12.7	10.5	10,038.20
Finland	41.2	32.0	26.8	33.4	13.2	6.3	2.0	30.0	15.1	0.8	2.5	8.7	14.3	17.7	36.3	19.7	9.5	8763.60
France	35.0	27.1	37.9	23.5	11.5	10.7	2.8	34.2	17.2	1.8	3.4	7.5	17.5	13.9	41.1	14.8	9.5	9985.80
Germany	32.8	31.7	35.5	21.0	16.6	11.4	5.3	28.7	16.9	2.1	2.8	9.9	17.7	18.4	35.4	13.7	11.2	9796.70
Greece	54.5	22.8	22.7	38.9	9.5	2.9	0.9	34.7	13.0	0.3	3.1	6.3	15.4	11.4	39.5	24	7.9	8515.30
Ireland	49.4	18.7	31.9	35.8	13.8	11.3	3.1	24.3	11.8	1.3	5.5	5.2	20.0	15.6	24.3	28.1	8.4	6612.40
Italy	45.8	24.6	29.6	29.9	13.4	9.3	3.7	31.0	12.7	1.4	2.2	9.7	19.6	18.8	32.9	15.4	7.3	8999.20
Japan	43.2	29.3	27.5	29.1	13.4	6.5	3.9	37.7	9.4	2.2	2.2	6.7	20.9	15.2	35.8	17	10.1	8901.20
Korea	57.9	19.2	22.9	41.7	12.5	4.8	4.3	27.1	9.5	2.8	1.1	4.3	16.5	17.7	24.8	32.7	6.8[c]	2486.80
The Netherlands	31.1	26.5	42.4	21.9	15	6.3	4.0	29.3	23.5	1.8	2.3	5.2	18.8	12.2	41.8	17.8	10	10,696.10
Norway	34.3	35.4	30.4	19.6	21.8	4.8	2.0	34.6	17.2	0.8	2.1	6.0	16.0	11.7	40.6	22.8	10.6	12,576.60
Portugal	49.8	23.1	27.1	33.4	11.7	6.1	2.2	33.8	12.8	0.8	1.5	4.1	22.5	17.3	30.9	22.8	6.9	5130.10
Spain	51.5	23.9	24.6	32.1	14.8	5.3	2.9	31.9	13.0	1.0	1.9	6.4	15.7	18.2	37.6	19.1	6.3	7287.50
Sweden	31.1	31.0	37.9	23.4	12.2	8.1	2.0	31.8	22.4	1.7	2.8	7.3	16.1	13.5	44.6	14.1	10	9953.50
Taiwan	48.6	24.3	27.2	30.3	18	6.5	5.0	29.4	10.8	3.5	1.6	8.8	17.8	24.1	25.8	18.3	6.4[c]	3355.70
UK	31.3	33.1	35.6	21.1	18.8	9.6	3.2	30.4	16.9	1.7	2.8	9.5	16.9	14.8	37.3	16.9	10	8636.40

(continued)

Table 2 Continued

	Skill categories			Innovation categories						ICT categories							Education	PPPpcGDP[c]
	Aggregate low[a]	Medium	Aggregate high[b]	Supplier-dominated	Scale-intensive	Specialized supplier	Science-based	Information-intensive	Non-market services	ICTPM	ICTPS	ICTUM	ICTUS	NICTM	NICTS	NICTO	Years	Current international dollar
United States	32.1	30.7	37.2	18.9	14.4	9.2	2.7	35.9	19.0	1.9	3.9	7.4	20.5	14.3	40	12.2	12.2	12,255.10
Average	40.6	27.5	31.9	27.1	14.8	7.3	3	31.8	16	1.5	2.6	6.7	18.2	15.5	36.4	19.1	9.4	8817.80
Std. Dev.	8.7	4.8	5.9	6.9	3.3	2.4	1.2	3.4	4.1	0.8	1.0	1.8	2.9	3.2	6.0	5.3	1.8	2602.30
Maximum	57.9	35.4	42.4	41.7	21.8	11.4	5.3	37.9	23.5	3.5	5.5	9.9	24.9	24.1	45.7	32.7	12.2	12,576.60
Minimum	31.1	18.7	22.7	18.4	9.5	2.9	0.9	24.3	9.4	0.3	1.1	4.1	14.1	10.4	24.3	12.2	6.3	2486.80

[a]Includes very low, low, and medium-low skill industries.
[b]Includes medium-high, high, and very high skill industries.
[c]Year of reference: 1980.
Source: Composition of economic activity: GGDC-60 Industry Database; Education: Bassanini and Scarpetta (2001) and Barro and Lee (2001); per capita income: IMF, World Economic Outlook Database (April 2008).
(N)ICT[P/U]{M/S/O}: (non) information and communication technology [producer/user]{manufacturing/services/other} industries.

belong to the first group of countries, whereas Portugal, Greece, and Korea are good representatives of the second, less developed group of countries.

With respect to the ICT classification, the results show that the two countries with lower per capita incomes, Korea and Taiwan, have the highest shares in ICT producing manufacturing (ICTPM) industries. These results are, however, mostly related to the radio and television receivers industry (ISIC 323), which accounts for about one half of gross value added in ICTPM industries in both countries, and to a lesser extent, to the electronic valves and tubes industry (ISIC 321), which contributes to approximately 20–25% of that production. This is in marked contrast with the more developed countries from our sample, such as Germany and the United States, which also present high shares of ICTPM industries, but in which the more important role is played by the scientific instruments industries (~40% of total GVA in ICTPM).[11]

The relative importance of ICTPM industries also explains why Korea and Taiwan present high output and employment shares in science-based industries, the industry group with more technological opportunities, despite being the less developed countries in the sample. As mentioned earlier, taxonomies sometimes "oversimplify" and hide important idiosyncrasies among countries, particularly when applying taxonomies based on developed countries to developing economies. Historical evidence, documented in Hobday (1995), shows that South Korean and Taiwanese firms began their catching up process in the 1960s and 1970s with the assembly of simple consumer goods, most notably transistors, radios and black and white televisions (classified as "science-based" industries), relying on buyers for technical assistance and market outlets. Thus, caution is required in interpreting the high shares of "science-based" industries in these countries in the given period.

The picture is different when one looks to the ICT producing services category. In this case, the countries which present higher shares are mostly wealthy countries, with the exception of Ireland and, to a lesser extent, Greece.[12] The same happens with respect to non-ICT services, and information-intensive and nonmarket services industries, the latter two representing categories from the innovation taxonomy. In all cases, the higher output shares found in more developed nations reflect the more advanced nature of the tertiarization processes in these countries, stemming from changes taking place from the 1960s onwards in trade, technology and demand factors (e.g. Feinstein, 1999; Peneder *et al.*, 2003; Castellacci, 2008).[13]

[11]In terms of employment, scientific instruments account for ~50% of total employment in ICTPM industries in Germany (45% in the US), whereas in Korea and Taiwan it does not surpass 5%. In line with the output figures, most of the employment in ICTPM industries in these latter countries occurs within the radio and television receivers industries (~54% of the total in Taiwan, and 41% in Korea).

[12]Korea and Taiwan, along with Portugal, show the lowest results.

[13]With regard to the employment variable, tertiarization can also be explained by the well-known cost-disease argument developed by Baumol (Baumol, 1967, 2001).

Table 3 Correlation coefficients

Classification	GVA shares		Employment shares	
	Education	Per capita GDP	Education	Per capita GDP
Skills				
Very high	0.50**	0.56***	0.65***	0.70***
Aggregate high[a]	0.55***	0.57***	0.74***	0.77***
Aggregate low[b]	−0.80***	−0.77***	−0.79***	−0.76***
Very low	−0.76***	−0.79***	−0.78***	−0.77***
Innovation				
Supplier-dominated	−0.72***	−0.75***	−0.76***	−0.76***
Scale-intensive	0.34	0.24	0.31	0.32
Specialized supplier	0.19	0.15	0.52**	0.36
Science-based	−0.24	−0.37	−0.17	−0.27
Information-intensive	0.31	0.44**	0.77***	0.69***
Non-market services	0.63***	0.71***	0.62***	0.75***
ICT				
ICT producing manufacturing	−0.21	−0.47**	−0.07	−0.33
ICT producing services	0.31	0.33	0.63***	0.62***
ICT using manufacturing	0.30	0.10	0.13	0.20
ICT using services	−0.08	−0.02	0.73***	0.55**
Non-ICT manufacturing	−0.56***	−0.64***	−0.57***	−0.61***
Non-ICT services	0.63***	0.79***	0.74***	0.85***
Non-ICT other	−0.37	−0.54**	−0.73***	−0.72***
Correlation education/GDPpc	0.82***		0.82***	

[a]Includes medium-high, high, and very high skill industries.
[b]Includes very low, low, and medium-low skill industries.
$N = 21$; ***, **Correlation is significant at the 0.01 and 0.05 levels, respectively (two-tailed test).

This impression is confirmed by the computation of Pearson bi-variate correlation coefficients, considering both data on value added and employment variables (cf. Table 3). The high positive relationship between education and per capita income and, inversely, the strong negative relationship of each of these variables and the relative shares of low-skilled and less innovative industries is clearly apparent. All the correlation coefficients relating education (or per capita GDP) to either the shares of low-skill or supplier-dominated industries are negative and strongly significant. The more odd results, namely, the negative correlation of science-based and ICT industry shares with both education and per capita GDP reflect the specificities of the Korean and Taiwanese economies. As indicated earlier, these countries show the highest shares of ICT producing manufacturing activities, which are also classified as "science-based", but these industries reflect mostly assembly-line production, that requires only minor skills of the workforce (e.g. Hobday, 1995).

3.3 Hierarchical clustering results

Cluster analysis involves a number of different procedures that allow for the division of a specific dataset into distinct groups, such that the degree of homogeneity is maximal if the observations belong to the same group and minimal otherwise. In the present study, because the dataset is relatively small, we use the hierarchical clustering approach to classify the individual observations into clusters of maximum homogeneity.

Hierarchical clustering identifies successive clusters by using previously established clusters. It can be either agglomerative or divisive, although the former is the most commonly used.[14] In the present case, we opted for the agglomerative approach, starting with each case as a separate cluster and successively merging the two closest clusters until a single, all-inclusive cluster remains.

The application of hierarchical agglomerative clustering requires the prior definition of a criterion to determine the distance or similarity between cases. We apply the cosine similarity criterion, although there is no clear-cut indication as to this measure's superiority in comparison to the others.[15] It also requires the definition of the rules for cluster formation. In the present case, we use the average linkage between groups method, also known as unweighted pair group method using arithmetic averages (UPGMA). This method defines the distance between two clusters as the average distance between all pairs of cases in the two different clusters.[16] Agglomerative clustering is applied to the standardized scores of the variables, rather than to their real values, because they are measured on different scales (industry share variables in percentage points, human capital in years, and per capita income in PPP current international US dollars).

Figure 1 presents the resulting dendrogram. The first vertical lines represent the smallest rescaled distance, which in the present case corresponds to the merging of Portugal and Spain on the one hand, and of Sweden and the United States, on the

[14]See Everitt *et al.* (2001) and Aldenderfer and Blashfield (1985) for more information on hierarchical cluster analysis and on cluster analysis procedures in general.

[15]Acknowledging the subjective nature of this choice, we have also considered distance measures, as well as the alternative similarity measure (the correlation of vectors). The resulting cluster solution was always the same.

[16]The UPGMA method seems to be preferable in comparison to single and complete linkage rules, since it uses information regarding all pairs of distances, and not just the nearest or the farthest.

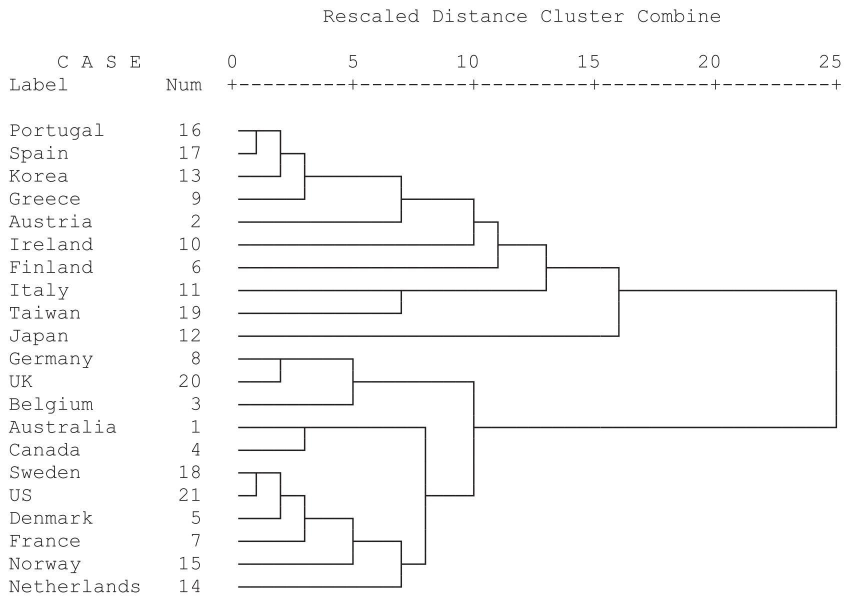

Figure 1 Dendrogram using average linkage between groups and the cosine similarity measure (1979).

other. Subsequent vertical lines represent merges at higher distances, until only one cluster, encompassing all cases, is obtained.

Generally, a good cluster solution is defined as being the one which precedes a sudden gap in the similarity (or distance) coefficient. In this case, the larger distance between sequential vertical lines occurs approximately between 15 and 25, suggesting that the best clustering solution splits the list of countries into two clusters:

1. A cluster formed by Portugal, Spain, South Korea, Greece, Austria, Ireland, Finland, Italy, Taiwan, and Japan (Cluster 1);
2. and a cluster including Germany, the UK, Belgium, Australia, Canada, Sweden, the United States, Denmark, France, Norway, and the Netherlands (Cluster 2).[17]

The clustering solution thus separates our sample into a cluster of highly developed countries (Cluster 2), characterized by high levels of education and per capita income, and relatively higher shares of innovative and high-skill industries, and a more heterogeneous cluster formed by relatively less developed countries (Cluster 1).

As can be seen from Table 4, there is indeed greater dispersion within Cluster 1, most particularly with regard to the ICT producing categories and to the per capita

[17]This result does not change when different linkage rules are considered.

Table 4 Descriptive statistics—Clusters 1 and 2 (1979, sectoral shares computed using gross value added)

	Skill categories (%)			Innovation categories (%)						ICT categories (%)							Education	PPPpcGDP[c]
	Aggregate low[a]	Medium	Aggregate high[b]	Suppleier-dominated	Scale-intensive	Specialized supplier	Science-based	Information-intensive	Non-market services	ICTPM	ICTPS	ICTUM	ICTUS	NICTM	NICTS	NICTO	Years	Current international dollar
Cluster 1																		
Average	48.6	24.3	27.1	33.3	13.5	6.5	3.0	31.2	12.5	1.6	2.4	6.6	18.3	17.2	32.4	21.5	8.0	7054.7
Std. Dev.	5.2	4.0	3.1	4.4	2.2	2.3	1.2	3.8	2.2	1.0	1.2	1.9	2.7	3.2	5.7	5.4	1.5	2637.0
Coefficient of variation	10.6	16.6	11.3	13.2	16.4	35.4	40.3	12.2	18.0	63.6	50.8	28.9	14.8	18.7	17.5	25.3	19.0	37.4
Cluster 2																		
Average	33.3	30.5	36.2	21.5	16.0	8.1	2.9	32.3	19.1	1.4	2.8	6.7	18.1	14.0	40.0	17.0	10.6	10420.6
Std. Dev.	1.9	3.4	4.1	2.1	3.8	2.4	1.2	3.0	2.5	0.5	0.7	1.8	3.2	2.2	3.8	4.3	1.0	1162.6
Coeffiicient of variation	5.6	11.1	11.4	9.6	23.6	29.7	41.1	9.3	13.2	35.8	23.6	26.5	17.5	16.0	9.4	25.1	9.4	11.2

Source: As in Table 2.

(N)ICT[P/U]{M/S/O}: (non) information and communication technology [producer/user]{manufacturing/services/other} industries.

Table 5 Absolute distances of countries included in Cluster 1 relative to average values of cluster 2

	Skill categories (%)			Innovation categories (%)						ICT categories (%)							Education	PPPpcGDP[c]
	Aggregate low[a]	Medium-	Aggregate high[b]	Supplier-dominate	Scale-intensive	Specialized supplier	Science-based	Information-intensive	Non-market services	ICTPM	ICTPS	ICTUM	ICTUS	NICTM	NICTS	NICTO	Years	Current international dollar
Austria	11.2	−5.5	−5.7	6.7	−1.1	−2.0	−0.5	−0.4	−2.6	0.0	−0.5	−0.6	1.8	2.3	−3.9	0.9	−0.3	74.4
Finland	7.9	1.5	−9.5	11.9	−2.8	−1.8	−0.9	−2.3	−4.1	−0.6	−0.4	2.0	−3.8	3.7	−3.7	2.8	−1.1	−1657.0
Greece	21.2	−7.7	−13.5	17.4	−6.5	−5.2	−1.9	2.3	−6.2	−1.1	0.2	−0.5	−2.7	−2.6	−0.4	7.0	−2.7	−1905.3
Ireland	16.2	−11.8	−4.3	14.2	−2.2	3.1	0.2	−8.0	−7.4	−0.1	2.6	−1.5	2.0	1.6	−15.7	11.1	−2.2	−3808.2
Italy	12.6	−5.9	−6.6	8.4	−2.6	1.1	0.8	−1.3	−6.4	0.0	−0.6	3.0	1.5	4.9	−7.1	−1.6	−3.3	−1421.3
Japan	9.9	−1.2	−8.8	7.5	−2.6	−1.7	1.0	5.4	−9.7	0.8	−0.7	0.0	2.8	1.2	−4.2	0.1	−0.5	−1519.3
Korea	24.6	−11.3	−13.3	20.2	−3.4	−3.3	1.4	−5.2	−9.6	1.4	−1.7	−2.4	−1.6	3.7	−15.2	15.8	−3.8	−7933.8
Portugal	16.5	−7.3	−9.2	11.9	−4.3	−2.0	−0.7	1.5	−6.3	−0.6	−1.3	−2.7	4.4	3.4	−9.1	5.9	−3.7	−5290.5
Spain	18.2	−6.6	−11.7	10.6	−1.2	−2.8	0.0	−0.4	−6.2	−0.4	−1.0	−0.3	−2.4	4.2	−2.3	2.2	−4.3	−3133.1
Taiwan	15.3	−6.2	−9.1	8.8	2.0	−1.6	2.1	−3.0	−8.4	2.1	−1.2	2.1	−0.3	10.1	−14.2	1.3	−4.2	−7064.9

[a]Includes very low, low, and medium-low skill industries.
[b]Includes medium-high, high, and very high skill industries.
[c]Year of reference: 1980.
Source: As in Table 2.
Notes: Absolute distance is calculated as the difference between the country's variable value and the corresponding average value of cluster 2. (N)ICT[P/U]{M/S/O}: (non) information and communication technology [producer/user]{manufacturing/services/other} industries.

income variable. Countries such as Austria, Finland, Italy, and Japan present considerably higher values for the income variable, close to the average value found for the countries included in Cluster 2, whereas Spain, Ireland, Portugal, and most notably, Korea and Taiwan, are very far behind (cf. Table 5). As a matter of fact, Austria, Japan, and Finland are classified in Cluster 1 mainly because of the composition of their economic activity, characterized by a greater reliance on supplier-dominated industries and the weaker relevance of high-skill industries comparatively to the countries included in Cluster 2. In contrast, countries such as Korea, Taiwan, and Portugal present substantial differences in relation to the more developed countries in virtually all the variables considered. These differences are particularly acute with respect to per capita income and human capital variables, and also in the (much higher) relevance of supplier-dominated industries.[18]

The higher dispersion in ICT producing categories in Cluster 1 reflects, furthermore, the economic specificities associated with the Asian countries in our sample, most particularly, Taiwan and Korea. The strong relevance of some assembly line ICT activities in these countries, together with relatively high shares of ICTPM industries in countries such as Austria and Ireland explains the higher average share of ICTPM industries in Cluster 1, when compared to Cluster 2. The inclusion in Cluster 1 of countries with marked differences in terms of per capita income might explain, in turn, the higher dispersion observed in ICT producing services activities.

4. Descriptive characterization of the growth and structural change processes of "relatively less developed countries" countries between 1979 and 2003

Countries in Cluster 1, "relatively less developed countries", which share some similar features in terms of economic structure in 1979, experienced very different processes of growth and structural change from that time onwards, which gave rise to a marked increase in their dissimilarities. Considerable differences arose with respect to GDP and labor productivity growth, with Korea, Ireland, and Taiwan experiencing very high growth rates, well above those observed in the other countries (cf. Table 6).

Furthermore, rapid growth experiences were intimately connected with strong structural transformation. The computation of Nickell and Lilien indices of structural change (cf. Table 7) reveals that the fastest growth countries—Korea, Taiwan, and Ireland—were simultaneously the countries with more rapid structural change

[18]It is worth highlighting, however, the contrasting evidence for Portugal, on the one hand, and for Taiwan and Korea, on the other, with respect to the relevance of science-based industries, which is considerably higher in these latter countries.

Table 6 GDP at constant prices, GDP per capita based on purchasing-power-parity and labor productivity (annual percentage change; 1979–2003)

	GDP constant prices	GDP per capita (PPP)	Labor productivity[a]
Austria	2.2	4.9	2.6
Finland	2.4	5.1	3.0
Greece	2.0	4.3	1.6
Ireland	5.0	7.4	5.0
Italy	1.8	4.8	1.6
Japan	2.3	5.0	3.4[b]
Korea	7.0	9.1	5.7[b]
Portugal	3.0	5.8	2.7
Spain	3.0	5.5	2.0
Taiwan	6.5	8.6	6.9[b]

[a]Labor productivity is defined as value added per hour worked.
[b]Reference period: 1979–2002.
Source: GDP: International Monetary Fund, World Economic Outlook Database, April 2008. Labor productivity: GGDC 60-Industry Database.

Table 7 Nickell and Lilien indices of structural change (1979–2003)[a]

	Nickell index	Lilien index
Austria	0.527	0.274
Finland	0.735	0.404
Greece	0.475	0.315
Ireland	0.885	0.566
Italy	0.505	0.381
Japan	0.463[b]	0.352[b]
Korea	0.882[b]	0.635[b]
Portugal	0.601	0.477
Spain	0.472	0.346
Taiwan	0.807[b]	0.574[b]

[a]Indices are calculated considering 56 sectors and sectoral proportions in value added.
[b]Reference period: 1979–2002.
Source: GGDC 60-Industry Database.

during the period under study.[19] In contrast, slow-growing countries such as Greece or Italy experienced much more modest changes. This is in broad agreement with the views expressed by the authors of the new structuralist approach (e.g. Pieper, 2000; Rada and Taylor, 2006), according to which rapid growth requires profound changes in the composition of economic activity and external trade.

The countries with faster structural change were also the ones experiencing more profound changes in the relative importance of the industry groups defined earlier (cf. Table 8). Korea, Ireland, and Taiwan were the countries where the decrease in the relative share of low-skill industries was more intense. The lower importance of these industries was compensated by a substantial increase in high-skill industries, particularly in the cases of Ireland and Korea. Ireland, Korea, and Taiwan also presented the largest decrease in supplier-dominated industries, which, as indicated earlier, are the industries facing lower technological opportunities. In contrast, relative shares of specialized supplier and science-based industries—Pavitt's top categories in technological and innovativeness potential—increased substantially (cf. Table 8).[20]

Moreover, these countries, along with Finland, presented the highest increases in ICT producing industries, showing, at the same time, important changes in the composition of those industries. In Taiwan and Korea, the radio and television receivers industry, which, as indicated earlier, accounted for about one half of total value added in ICTPM in 1979, has at the end of the period only a minor contribution (5.5% and 2.5% in gross value added in Korea and Taiwan, respectively). In contrast, the relative importance of electronic valves and tubes and office machinery increased substantially, representing as a whole, more than 70% of total value added in ICTPM industries (cf. Figure 2).[21] A strong increase in the electronic valves and tubes industry is also experienced by Ireland, rising from 3.9% to 22.5% of gross value added in 2003.

Given the profound changes in the structure of their economies, it is no surprise that Korea, Ireland, and Taiwan have been able to significantly modify their situation in comparison to the more developed countries included in Cluster 2. Indeed, these countries have dramatically reduced the gap regarding the relative importance of low-skill and supplier-dominated industries, and converged, at the same time, in the more technological and skill-intensive categories. In the case of Ireland, in particular, not only was there a drastic reduction in the low-tech and low-skill industries distances, but also a substantial increase in the already positive gap with respect to specialized supplier and science-based industries.

Our findings seem to indicate furthermore that the influence of structural change on economic growth depends on its association with technological change. The case

[19]See Lilien (1982) and Nickell (1985) for details on the computation of these indices.

[20]In Taiwan and Korea, there was however a small decline in the relative importance of science-based industries.

[21]More precisely, 73.9% in Korea and 82.4% in Taiwan.

Table 8 Change in industry output shares between 1979 and 2003 (%)

	Skill categories			Innovation categories						ICT categories						
	Aggregate low[a]	Medium	Aggregate high[b]	Supplie-dominate	Scale-intensive	Specialized supplier	Science-based	Information-intensive	Non-market services	ICTPM	ICTPS	ICTUM	ICTUS	NICTM	NICTS	NICTO
Austria	−9.4	3.8	5.5	−3.9	−3.7	4.7	−0.4	4.0	−0.6	0.0	1.5	0.1	2.2	−4.0	5.6	−5.3
Finland	−14.1	1.9	12.2	−11.2	−4.5	6.9	0.2	5.1	3.4	3.7	3.0	−2.4	1.1	−5.9	9.1	−8.5
Greece	−9.1	2.0	7.2	−7.4	−1.1	0.2	−0.1	4.1	4.4	−0.1	0.1	−2.7	2.2	−3.8	10.4	−6.2
Ireland	−21.8	−0.9	22.8	−14.5	−5.6	5.5	11.6	0.2	2.8	3.0	2.6	0.9	0.6	5.2	3.2	−15.4
Italy	−12.4	3.8	8.6	−7.2	−3.2	1.8	−1.5	7.1	2.8	−0.6	1.8	−3.5	3.8	−7.0	10.5	−5.1
Japan[c]	−13.0	5.7	7.3	−5.6	−3.1	1.5	−1.2	7.0	1.4	0.1	0.4	−1.8	3.8	−5.8	8.5	−5.2
Korea[c]	−23.0	6.6	16.4	−17.5	4.6	4.8	−0.6	4.9	3.8	1.4	2.1	1.1	1.3	0.0	10.7	−16.7
Portugal	−15.8	2.0	13.8	−8.5	−1.7	−1.5	−0.7	1.9	10.7	−0.2	2.3	−0.2	−2.3	−5.7	15.5	−9.4
Spain	−7.5	−0.6	8.2	−1.7	−4.3	1.8	−0.7	1.6	3.4	−0.6	2.2	−2.3	2.0	−6.6	9.1	−3.8
Taiwan[c]	−19.2	5.9	13.3	−15.0	−5.7	4.2	−1.9	14.5	3.9	2.4	1.4	−4.4	10.4	−9.3	11.1	−11.5

[a]Includes very low, low, and medium-low skill industries.
[b]Includes medium-high, high, and very high skill industries.
[c]Reference period: 1979–2002.
(N)ICT[P/U]{M/S/O}: (non) information and communication technology [producer/user]{manufacturing/services/other} industries.

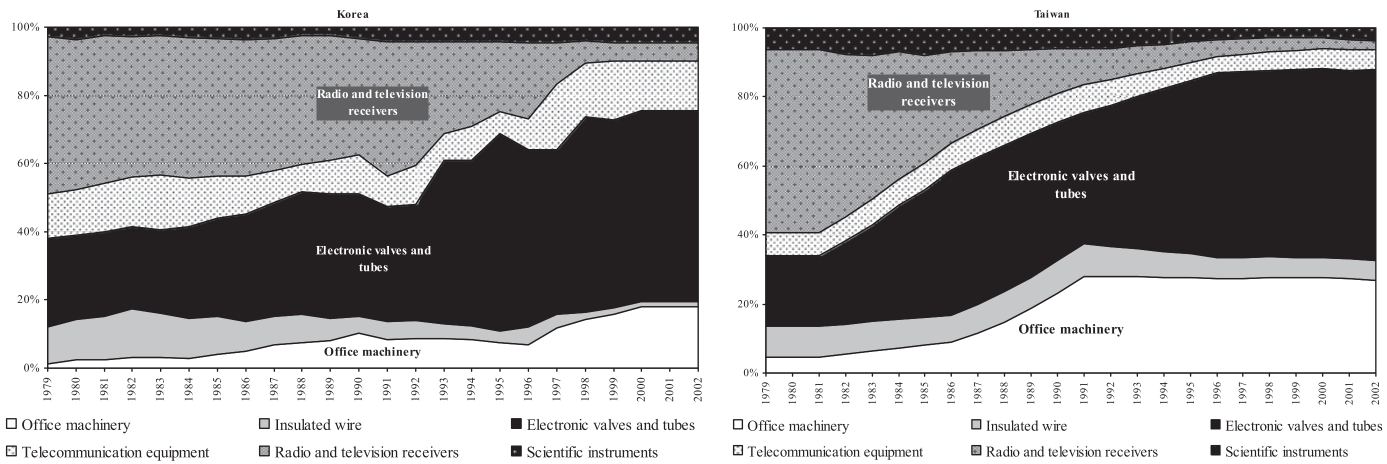

Figure 2 Evolution of the distribution of gross value added in ICT producing manufacturing, Korea and Taiwan, 1979–2002.

Table 9 Average number of years of formal education of the working age population (25–64 years) (1979–2003)

	Years		Percent change	Education gap[a]		
	1979	2003	1979–2003	1979	2003	Var. (years)
Austria	10.3	12.2	18.8	−0.3	−0.1	0.2
Finland	9.5	12.5	**31.3**	−1.1	0.1	1.2
Greece	7.9	10.4	**32.0**	−2.7	−1.9	0.8
Ireland	8.4	10.9	**29.7**	−2.2	−1.5	0.7
Italy	7.3	10.4	**42.7**	−3.3	−1.9	1.4
Japan	10.1	12.7	**25.8**	−0.5	0.3	0.8
Korea	6.8	10.8	**59.3**	−3.8	−1.5	2.3
Portugal	6.9	8.0	16.6	−3.7	−4.3	−0.6
Spain	6.3	9.7	**54.4**	−4.3	−2.6	1.7
Taiwan	6.4	8.8	**38.9**	−4.2	−3.5	0.7

[a]The education gap is defined as the difference between the country’s value and the average of countries included in Cluster 2.
Bold highlights countries with the highest increases in the average number of years of education.

of Portugal is rather illustrative of this point. Despite showing relatively fast structural change between 1979 and 2003, Portugal did not significantly change the composition of its economy in terms of the industry groups considered. The country was able to reduce the relative importance of low-skill and supplier-dominated industries and to increase high-skill industry shares, but the rate at which this transformation took place was relatively low. Moreover, and quite significantly, the most important change observed during this period refers to non-market services, which increased their relative importance in ~11% points. This has probably had an influence on the relatively poor performance of the Portuguese economy, when compared to other countries in the sample.

Considerable changes in education also came into play during this period.[22] All the countries increased the average number of years of formal education of the working age population, expanding human capital stocks (cf. Table 9). However, the rates at which this increase took place differed significantly across countries.

[22]In order to get a full series of education data we extended Bassanini and Scarpetta’s (2001) estimates up to 2003 using the author’s methodology. We also applied this procedure to Korean and Taiwanese data, considering Barro and Lee’s (2001) estimates. The complete data set and some details on the calculus procedure can be found in Table A2 in Appendix A.

Korea shows once more an impressive performance, along with Spain, Italy, and Taiwan. Portugal, on the other hand, presents the weakest increase in the average number of years of formal education, and is the only country which widens the gap in comparison to the countries included in Cluster 2.

5. Regression analysis

5.1 The model

The empirical model is based on the typical cross-country catch-up equation (cf. Barro and Sala-i-Martin, 2003), which can be formulated as follows:

$$y_{it} - y_{it-k} = \beta y_{it-k} + \delta x_{it} + \mu_i + \varepsilon_{it}. \tag{1}$$

In this expression, y_{it} is the logarithm of labor productivity, defined as the value added over employment in hours for country i in period t, x_{it} represents a vector of variables influencing economic growth, μ_i represents the unobservable country-specific effect, and ε_{it} is the error term.

Equation (1) can be rewritten as:

$$y_{it} = \beta_1 y_{it-k} + \delta x_{it} + \mu_i + \varepsilon_{it}, \tag{2}$$

where $\beta_1 = 1 + \beta$. This is a dynamic specification, since it includes the lagged dependent variable among the regressors. It requires special instrumentation of the lagged endogenous variable, for which we use the one-step GMM estimator developed by Arellano and Bond (1991).[23]

Differencing equation (2), the country specific effects are removed and the following equation is obtained:

$$y_{it} - y_{it-k} = \beta_1(y_{it-k} - y_{it-2k}) + \delta(x_{it} - x_{it-k}) + (\varepsilon_{it} - \varepsilon_{it-k}). \tag{3}$$

Equation (3) is estimated using GMM, considering both 1- and 5-year intervals ($k = 1$ and 5), and assuming different specifications for the explanatory variables.

Given our previous analysis, the main explanatory variables reflect changes in economic structure. More precisely, the variables considered are industry group shares of some of the taxonomical categories described earlier (x_{1i}) and their changes over time (Δx_{1i}).[24] Both variables are expressed in lagged values so that causality runs from industrial structure to productivity growth, and not the other way around. According to the theory, the coefficients associated with these variables are expected to be positive when industry shares refer to high-skill, specialized supplier and

[23]We opted in favor of the one-step formulation of Arellano-Bond GMM estimators, since there is evidence regarding downward bias problems in the estimates of standard errors when using the two-step estimator (Arellano and Bond, 1991; Islam, 2000).

[24]Δ represents first differences.

science-based industries, given their high productivity growth rates and the indirect positive effects they generate to other industries, through producer and user-related spillovers. More precisely, products and innovations originating in skills and technology-intensive sectors are likely to be conducive to productivity gains in other industries which use these products or find new applications for the innovations developed, and therefore increase productivity. Inversely, a negative sign is expected when low-skill, supplier-dominated industry shares are considered.[25] A positive sign is also expected with respect to ICT related industries, given their role under the current techno-economic paradigm.

Along with these variables, which reflect the qualitative nature of the process of structural change undertaken, we also include the Nickell index of structural change (*SC*), which takes into account the pace at which changes in the composition of economic activity took place. A positive impact is expected, assuming that rapid growth requires profound changes in the composition of economic activity, as discussed earlier.

A number of control variables are also included. Following the arguments developed in Section 2, we control for the influence of the countries' human and physical capital investments, which, as indicated earlier, are prior requirements for the adoption and creation of technology. The human capital variable (*EDUC*) is expressed by the average years of education of the working age population, and its variation over time ($\Delta EDUC$). Physical capital accumulation is taken into account through the inclusion of both the share of investment in GDP (*INV*), and its change between $t-k$ and $t(\Delta INV)$.[26] In line with our earlier discussion, the coefficients associated to physical and human capital variables are expected to be positive. Finally, we control for business cycle effects including time dummies in all equations.[27]

The estimations are performed using the sample of countries included in Cluster 1 over the 1980–2003 period.[28] The data source for labor productivity and industry

[25]This should not be seen as meaning that supplier-dominated (or low-medium technology) industries do not contribute to productivity growth. On the contrary, supplier-dominated firms do generate production processes that have considerable aggregate impact (Heidenreich, 2009). Nevertheless, these industries tend to lag in product and service innovation when compared with their high technology, science-based counterparts, explaining therefore their relatively lower contribution to overall productivity growth (cf. Kirner *et al.*, 2009).

[26]The control variables are also expressed in lagged values in order to mitigate possible endogeneity problems.

[27]In previous estimations, we also included the employment rate to check for country specific differences in the business cycle. Since this variable was never statistically significant and could directly influence labor productivity growth, it was excluded in the present framework.

[28]One observation was lost (1979), because data on employment and investment variables was only available from 1980 onwards. Data regarding Taiwan, Korea and Japan refer to the 1980–2002 period.

shares is the 60-Industry GGDC Database. Data on education are taken from Bassanini and Scarpetta (2001) and Barro and Lee (2001), and extended up to 2003 using OECD *Education at a Glance* data, as indicated in the previous section. Data on gross fixed capital formation are from the *OECD Factbook 2008: Economic, Environmental and Social Statistics*, with the exception of Taiwan, whose data were taken from the Taiwanese official government statistics.[29]

5.2 Estimation results

In Tables 10–13, we report one-step GMM estimates of the dynamic growth equations.

The critical assumption underlying the GMM estimations, that is the lack of any second-order autocorrelation in the residuals from the model in first differences, is never rejected by the robust m_2 statistics computed.[30]

The estimated coefficients show relative stability throughout all estimations. The coefficient of the lagged productivity variable is always positive and inferior to 1, which conveys the typical conditional convergence result, according to which countries with lower initial productivity levels present, on average, higher growth rates.

Regarding the control variables, the coefficient for the lagged education level is positive and statistically significant in several equations using 1-year lags, but is never significant when 5-year lags are considered. The change in the education variable is never statistically significant. With respect to the physical capital variables, the variation in the rate of investment turns up with the expected positive sign in all estimations and is significant in most cases, supporting the idea that the renewal rate of the capital stock influences growth positively. The lagged investment rate shows in some of the 1-year lag estimations a negative and significant coefficient. This seemingly counter-intuitive result may reflect the fact that some of the slowest growing countries in our sample, such as Japan and Portugal, present relatively high investment rates.[31]

With more relevance for the present work, the results confirm our premise according to which structure influences productivity growth, irrespective of the lag chosen or the variable used in the computation of industry shares (employment or gross value added). In global terms, the coefficients for the structural variables turn up with the expected signs and are, in most cases, statistically significant.

[29]Available on-line at: http://eng.dgbas.gov.tw.

[30]The m_2 statistic is used rather than the more well-known Sargan test, due to the latter's tendency to over-reject the null hypothesis of serially uncorrelated errors in the case of one-step GMM estimations (Arellano and Bond, 1991).

[31]The average investment rate in Japan and Portugal during the period under study is 29% and 26%, respectively, whereas in Ireland and Taiwan the corresponding figures are 20% and 23%.

Table 10 The effect of structural change on productivity growth (y_t) (GVA, 1-period lag, GMM estimates, all variables in first differences)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
$y_{i,t-1}$	0.959***	0.963***	0.899***	0.909***	0.903***	0.912***	0.901***	0.899***	0.954***	0.955***	0.956***	0.955***	0.933***	0.934***	0.936***	0.934***	0.959***	0.964***
	(46.153)	(47.175)	(27.017)	(28.414)	(23.004)	(24.783)	(24.928)	(27.699)	(32.902)	(38.284)	(56.852)	(54.810)	(42.745)	(41.745)	(44.721)	(45,784)	(2.827)	(27.125)
$EDUC_{i,t-1}$	0.018*	0.016*	0.035**	0.033**	0.020**	0.020***	0.011	0.014	0.022**	0.021*	0.015	0.014	0.002*	0.020*	0.003	0.006	0.019**	0.016*
	(1.713)	(1.697)	(2.596)	(2.359)	(2.451)	(2.953)	(0.885)	(1.413)	(2.011)	(1.822)	(1.307)	(1.564)	(1.950)	(1.918)	(0.262)	(0.510)	(2.143)	(1.612)
$\Delta EDUC_{i,t-1}$	−0.045	−0.047	−0.039	−0.042	−0.031	−0.038	−0.012	−0.025	−0.063	−0.063	−0.040	−0.044	−0.042	−0.047	−0.021	−0.027	−0.029	−0.028
	(−0.880)	(−0.920)	(−0.740)	(−0.786)	(−0.662)	(−0.802)	(−0.371)	(−0.605)	(−1.399)	(−1.338)	(−0.794)	(−0.905)	(−0.751)	(−0.880)	(−0.481)	(−0.536)	(−0.580)	(−0.522)
$INV_{i,t-1}$	−0.239***	−0.206**	−0.286***	−0.264**	−0.213*	−0.194*	−0.122	−0.096	−0.217**	−0.196**	−0.229***	−0.184**	−0.159	−0.141	−0.113	−0.096	−0.186*	−0.146
	(−2.719)	(0.450)	(−2.638)	(−2.498)	(−1.863)	(−1.796)	(−0.911)	(−0.750)	(−2.487)	(−2.085)	(−3.346)	(−2.216)	(−1.449)	(−1.221)	(−1.401)	(−1.150)	(−1.726)	(−1.196)
$\Delta INV_{i,t-1}$	0.437***	0.450***	0.517***	0.511***	0.442**	0.437***	0.317*	0.282***	0.383**	0.402***	0.429**	0.432***	0.349**	0.382***	0.336**	0.360***	0.367**	0.374***
	(2.750)	(3.748)	(3.189)	(3.451)	(2.549)	(2.806)	(1.612)	(2.889)	(2.629)	(3.556)	(2.859)	(3.846)	(2.118)	(2.983)	(2.301)	(2.662)	(2.334)	(2.926)
$SC_{i,t/t-1}$		0.310**		0.161		0.226*		0.314*		0.264*		0.313**		0.280***		0.353***		0.323***
		(2.496)		(1.399)		(1.595)		(1.795)		(1.809)		(2.491)		(2.544)		(3.389)		(2.754)
Skills																		
$Agghigh_{i,t-1}$			0.767***	0.671**														
			(2.889)	(2.404)														
$\Delta Agghigh_{i,t-1}$			0.083	0.043														
			(0.311)	(0.172)														
$Agg.low_{i,t-1}$					−0.536*	−0.461												
					(−1.863)	(−1.550)												
$\Delta Agglow_{i,t-1}$					−0.081	0.082												
					(−0.239)	(0.232)												
Innovation																		
$Sc.based_{i,t-1}$									0.436*	0.371*								
									(2.069)	(1.667								
Δ $Sc.based_{i,t-1}$									−0.441	−0.414								
									(−1.028)	(−0.903)								
$Sp.supp_{i,t-1}$											0.081	0.133						
											(0.314)	(0.604)						
Δ $Sp.supp_{i,t-1}$											−0.321	−0.286						
											(−1.418)	(−1.192)						
$Sup.domin_{i,t-1}$							−0.790**	−0.744**										
							(−2.129)	(−1.960)										
$\Delta Sup.domin_{i,t-1}$							0.173	0.348										
							(0.462)	(0.919)										

(continued)

Table 10 Continued

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
ICT																		
$ICTPM_{i,t-1}$													0.691	0.649	0.884	0.734		
													(1.221)	(1.266)	(1.483)	(1.350)		
$\Delta ICTPM_{i,t-1}$													0.810**	0.887**	0.954**	0.965**		
													(2.243)	(2.036)	(2.331)	(2.139)		
$ICTPS_{i,t-1}$													−0.168	0.002			−0.482	−0.427
													(−0.352)	(0.051)			(−0.711)	(−0.691)
$\Delta ICTPS_{i,t-1}$													0.574	0.249			0.922	0.662
													(1.262)	(0.685)			(1.248)	(1.004)
$ICTUM_{i,t-1}$															0.249	0.771		
															(0.990)	(0.792)		
$\Delta ICTUM_{i,t-1}$															−0.667	−0.413		
															(−0.854)	(−0.512)		
$ICTUS_{i,t-1}$																	−0.325*	−0.469**
																	(−1.576)	(−2.415)
$\Delta ICTUS_{i,t-1}$																	−0.057	0.060
																	(−0.155)	(0.192)
No. of observations	227	227	217	217	217	217	217	217	217	217	217	217	217	217	217	217	217	217
No. of countries	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
m_2	−0.389	−0.400	−0.358	−0.367	−0.372	−0.381	−0.370	−0.381	−0.396	−0.403	−0.383	−0.395	−0.388	−0.393	−0.396	−0.399	−0.396	−0.407

***,**, *Statistically significant at 1%, 5%, and 10%, respectively.

Notes: (i) Time dummies are included in all equations; (ii) asymptotic standard errors robust to general cross-section and time series heteroskedasticity are reported in parentheses; (iii) GMM estimates are all one step; (iv) lagged values of the dependent variable and the explanatory variables are used as instruments.

Table 11 The effect of structural change on productivity growth (hours, 1-period lag, GMM estimates, all variables in first differences)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
$y_{i,t-1}$	0.959***	0.963***	0.943***	0.948***	0.940***	0.945***	0.935***	0.936***	0.950***	0.950***	0.942***	0.945***	0.974***	0.980***	0.964***	0.971***	0.936***	0.940***
	(46.153)	(47.175)	(40.665)	(43.709)	(26.390)	(26.734)	(48.843)	(54.328)	(35.752)	(44.098)	(46.777)	(41.475)	(63.445)	(67.041)	(65.171)	(68.043)	(30.933)	(36.235)
$EDUC_{i,t-1}$	0.018*	0.016*	0.021*	0.021*	0.019*	0.018**	0.009	0.006	0.018	0.015	0.013	0.011	0.001	0.000	−0.004	−0.004	0.005	0.003
	(1.713)	(1.697)	(1.693)	(1.827)	(1.715)	(2.136)	(0.907)	(0.564)	(1.155)	(0.981)	(0.892)	(0.873)	(0.208)	(0.048)	(−0.965)	(−0.977)	(0.300)	(0.252)
$\Delta EDUC_{i,t-1}$	−0.045	−0.047	−0.043	−0.048	−0.045	−0.048	−0.039	−0.038	−0.046	−0.044	−0.044	−0.045	−0.017	−0.012	−0.022	−0.017	−0.016	−0.018
	(−0.880)	(−0.920)	(−0.823)	(−0.921)	(−0.816)	(−0.896)	(−0.944)	(−0.984)	(−0.936)	(−0.968)	(−0.927)	(−0.944)	(−0.686)	(−0.435)	(−1.000)	(−0.685)	(−0.317)	(−0.304)
$INV_{i,t-1}$	−0.239***	−0.206**	−0.218**	−0.191**	−0.237**	−0.201**	−0.181*	−0.139	−0.220	−0.184	−0.208**	−0.172	−0.001	0.009	−0.001	0.000	−0.131	−0.079
	(−2.719)	(0.450)	(−2.325)	(−1.988)	(−2.607)	(−2.098)	(−1.761)	(−1.176)	(−1.542)	(−1.249)	(−2.056)	(−1.570)	(−0.013)	(0.151)	(−0.042)	(0.014)	(−1.400)	(−0.818)
$\Delta INV_{i,t-1}$	0.437***	0.450***	0.416***	0.432***	0.415***	0.431***	0.412***	0.333**	0.427*	0.422**	0.439***	0.436***	0.127	0.200*	0.240*	0.278**	0.241*	0.260**
	(2.750)	(3.748)	(2.690)	(3.500)	(2.403)	(3.182)	(2.728)	(2.596)	(1.900)	(2.311)	(3.785)	(5.009)	(0.984)	(1.919)	(1.845)	(2.548)	(1.785)	(1.976)
$SC_{i,t/t-1}$		0.310**		0.299***		0.331**		0.418***		0.271***		0.261*		0.324***		0.278***		0.417***
		(2.496)		(2.710)		(2.466)		(3.704)		(3.221)		(1.901)		(3.586)		(3.599)		(2.656)
Skills																		
$Agghigh_{i,t-1}$			0.420**	0.358*														
			(2.116)	(1.724)														
$\Delta Agghigh_{i,t-1}$			−0.377	−0.390														
			(−1.042)	(−1.105)														
$Agg.low_{i,t-1}$					−0.179	−0.165												
					(−0.828)	(−0.772)												
$\Delta Agglow_{i,t-1}$					0.356	0.296												
					(0.601)	(0.515)												
Innovation																		
$Sc.based_{i,t-1}$									−0.203	0.149								
									(−0.138)	(0.107)								
Δ $Sc.based_{i,t-1}$									0.412	0.100								
									(0.213)	(0.048)								
$Sp.supp_{i,t-1}$											0.283	0.274						
											(0.438)	(0.535)						
Δ $Sp.supp_{i,t-1}$											−1.206	−0.925						
											(−1.630)	(−1.042)						
$Sup.domin_{i,t-1}$							−0.157	−0.181										
							(−1.146)	(−1.607)										
$\Delta Sup.domin_{i,t-1}$							−0.594*	−0.564										
							(−1.723)	(−1.401)										

(continued)

Table 11 Continued

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
ICT																		
$ICTPM_{i,t-1}$													1.007*	0.580	1.699***	1.220**		
													(1.938)	(1.077)	(3.003)	(2.581)		
$\Delta ICTPM_{i,t-1}$													0.319	0.885	0.865	1.197		
													(0.316)	(0.949)	(0.835)	(1.207)		
$ICTPS_{i,t-1}$													−1.636**	−1.259			−2.042	−1.625
													(−2.320)	(−1.607)			(−1.254)	(−0.977)
$\Delta ICTPS_{i,t-1}$													1.485	0.466			0.334	−0.616
													(0.948)	(0.257)			(0.114)	(−0.224)
$ICTUM_{i,t-1}$															−0.611***	−0.436**		
															(−2.969)	(−2.001)		
$\Delta ICTUM_{i,t-1}$															−0.959	−0.735		
															(−1.276)	(−0.959)		
$ICTUS_{i,t-1}$																	0.304	0.296
																	(0.990)	(1.316)
$\Delta ICTUS_{i,t-1}$																	−0.367	−0.733
																	(−0.635)	(−1.361)
No. of observations	227	227	217	217	217	217	217	217	217	217	217	217	217	217	217	217	217	217
No. of countries	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
m_2	−0.389	−0.400	−0.388	−0.400	−0.384	−0.397	−0.382	−0.393	−0.395	−0.401	−0.391	−0.401	−0.414	−0.419	−0.391	−0.402	−0.405	−0.409

***, **, *Statistically significant at 1%, 5%, and 10%.

Notes: (i) Time dummies are included in all equations; (ii) asymptotic standard errors robust to general cross-section and time series heteroskedasticity are reported in parentheses; (iii) GMM estimates are all one step; (iv) lagged values of the dependent variable and the explanatory variables are used as instruments.

Table 12 The effect of structural change on productivity growth (GVA, 5-period lag, GMM estimates, all variables in first differences)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
$y_{i,t-1}$	0.988***	0.971***	0.858***	0.868***	0.790***	0.805***	0.928***	0.909***	0.916***	0.925***	0.922***	0.919***	0.842***	0.848***	0.782***	0.809***	0.869***	0.869***
	(10.325)	(13.161)	(9.807)	(15.405)	(10.426)	(9.767)	(10.736)	(16.492)	(7.530)	(8.723)	(8.240)	(9.760)	(9.755)	(10.071)	(5.218)	(6.691)	(12.490)	(12.249)
$EDUC_{i,t-1}$	−0.079	−0.060	−0.012	0.003	−0.049	−0.029	−0.084	−0.066	−0.004	−0.007	−0.071	−0.071	−0.040	−0.052	−0.057	−0.055	−0.050	−0.042
	(−1.472)	(−1.511)	(−0.363)	(0.105)	(−1.162)	(−0.903)	(−1.572)	(−1.462)	(−0.091)	(−0.195)	(−1.189)	(−1.450)	(−1.036)	(−1.585)	(1.524)	(−1.615)	(−1.227)	(−1.366)
$\Delta EDUC_{i,t-1}$	−0.034	−0.039	−0.007	−0.019	0.006	0.003	−0.005	−0.020	−0.092	−0.084	−0.062	−0.052	−0.045	−0.041	−0.019	−0.030	−0.094	−0.098
	(−0.394)	(−0.657)	(−0.102)	(−0.370)	(0.155)	(0.137)	(−0.076)	(−0.479)	(−1.404)	(−1.428)	(−0.737)	(−0.742)	(−0.927)	(−0.973)	(−0.209)	(−0.455)	(−1.308)	(−1.494)
$INV_{i,t-1}$	0.343	0.319	0.091	0.268	0.511	0.411	0.757	0.651	−0.153	−0.043	0.252	0.488	0.589	0.759*	0.706	0.714*	0.181	0.113
	(0.614)	(0.771)	(0.168)	(0.763)	(1.114)	(1.110)	(1.232)	(1.359)	(−0.367)	(−0.119)	(0.338)	(0.791)	(1.100)	(1.807)	(1.311)	(1.747)	(0.412)	(0.329)
$\Delta INV_{i,t-1}$	0.612*	0.477	0.426	0.347*	0.566**	0.335	0.752**	0.500	0.229	0.202	0.576	0.500	0.577*	0.576**	0.472	0.467*	0.509*	0.445*
	(1.692)	(1.527)	(1.533)	(1.725)	(2.192)	(1.398)	(1.906)	(1.569)	(0.823)	(0.761)	(1.181)	(1.285)	(1.864)	(2.276)	(1.485)	(1.884)	(1.906)	(1.910)
$SC_{i,t/t-1}$		0.614***		0.678***		0.639***		0.578**		0.357**		0.531**		0.439**		0.372		0.521**
		(2.827)		(3.140)		(3.081)		(2.585)		(2.122)		(2.206)		(2.337)		(1.580)		(2.570)
Skills																		
$Agghigh_{i,t-1}$			1.736***	1.508**														
			(3.252)	(2.599)														
$\Delta Agghigh_{i,t-1}$			0.564	−0.228														
			(0.915)	(−0.338)														
$Agg.low_{i,t-1}$					−2.056**	−1.986***												
					(−2.469)	(−2.683)												
$\Delta Agglow_{i,t-1}$					−1.330*	−0.507												
					(−1.801)	(−0.704)												
Innovation																		
$Sc.based_{i,t-1}$									2.522***	2.126***								
									(3.169)	(2.731)								
$\Delta\ Sc.based_{i,t-1}$									2.276***	2.017**								
									(3.788)	(2.346)								
$Sp.supp_{i,t-1}$											2.939**	2.595***						
											(2.292)	(3.156)						
$\Delta\ Sp.supp_{i,t-1}$											−0.100	−0.247						
											(−0.103)	(−0.513)						
$Sup.domin_{i,t-1}$							−1.552*	−1.442**										
							(−2.520)	(−2.759)										
$\Delta Sup.domin_{i,t-1}$							−0.935	−0.363										
							(−0.993)	(−0.405)										

(continued)

Table 12 Continued

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
ICT																		
$ICTPM_{i,t-1}$													5.308***	5.631***	6.129***	5.580***		
													(3.949)	(4.357)	(2.722)	(3.009)		
$\Delta ICTPM_{i,tv1}$													1.506	1.446	2.340	1.928		
													(1.445)	(1.376)	(1.543)	(1.384)		
$ICTPS_{i,t-1}$													−2.175	−1.445			−0.712	1.671
													(−0.795)	(−0.622)			(−0.424)	(0.860)
$\Delta ICTPS_{i,t-1}$													0.301	−0.611			3.495***	3.294***
													(0.213)	(−0.525)			(2.640)	(3.054)
$ICTUM_{i,t-1}$															1.283	0.351		
															(0.669)	(0.220)		
$\Delta ICTUM_{i,t-1}$															−1.990	−1.760		
															(−1.076)	(−1.042)		
$ICTUS_{i,t-1}$																	0.932	1.070
																	(1.275)	(1.280)
$\Delta ICTUS_{i,t-1}$																	0.871	0.577
																	(1.220)	(0.885)
No. of observations	187	187	187	187	187	187	187	187	187	187	187	187	187	187	187	187	187	187
No. of countries	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
m_2	−0.401	−0.266	−0.258	−0.258	−0.225	−0.221	−0.283	−0.243	−0.314	−0.246	−0.274	−0.235	−0.172	−0.136	−0.096	−0.112	−0.357	−0.292

***, **, *Statistically significant at 1%, 5%, and 10%; *T*-values between brackets.

Notes: (i) Time dummies are included in all equations; (ii) asymptotic standard errors robust to general cross-section and time series heteroskedasticity are reported in parentheses; (iii) GMM estimates are all one step; (iv) lagged values of the dependent variable and the explanatory variables are used as instruments.

Table 13 The effect of structural change on productivity growth (hours, 5-period lag, GMM estimates, all variables in first differences)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
$y_{i,t-1}$	0.988***	0.971***	0.938***	0.954***	0.995***	0.979***	0.972***	0.974***	0.963***	0.964***	0.851***	0.879***	0.834***	0.855***	0.756***	0.787***	0.966***	0.982***
	(10.325)	(13.161)	(10.598)	(11.957)	(7.940)	(10.610)	(9.829)	(11.456)	(8.999)	(12.385)	(4.861)	(5.723)	(6.446)	(6.262)	(8.480)	(9.098)	(15.653)	(16.989)
$EDUC_{i,t-1}$	−0.079	−0.060	−0.042	−0.052	−0.056	−0.041	−0.025	−0.028	−0.068	−0.064	−0.086	−0.069	−0.031	−0.032	−0.036	−0.037	−0.010	−0.022
	(−1.472)	(−1.511)	(−1.012)	(−1.488)	(−0.993)	(−1.101)	(−0.535)	(−0.691)	(−1.267)	(−1.254)	(−1.626)	(−1.451)	(−1.061)	(−1.204)	(−1.282)	(1.363)	(−0.209)	(−0.516)
$\Delta EDUC_{i,t-1}$	−0.034	−0.039	−0.029	−0.033	−0.015	−0.016	−0.045	−0.039	−0.030	−0.038	−0.070	−0.059	−0.067	−0.059	−0.095**	−0.087**	−0.037	−0.033
	(−0.394)	(−0.657)	(−0.438)	(−0.749)	(−0.296)	(−0.429)	(−0.885)	(−0.919)	(−0.333)	(−0.592)	(−0.692)	(−0.757)	(−1.486)	(−1.363)	(−1.297)	(−1.196)	(−0.821)	(−0.841)
$INV_{i,t-1}$	0.343	0.319	0.176	0.368	0.375	0.178	0.323	0.227	0.009	0.195	0.314	0.300	0.018	0.073	0.179	0.270	−0.399	−0.211
	(0.614)	(0.771)	(0.366)	(0.954)	(0.683)	(0.401)	(0.834)	(0.806)	(0.014)	(0.356)	(0.587)	(0.811)	(0.040)	(0.181)	(0.428)	(0.718)	(−0.678)	(−0.455)
$\Delta INV_{i,t-1}$	0.612*	0.477	0.550**	0.521*	0.773**	0.470	0.492*	0.361*	0.432	0.356	0.273	0.214	0.093	0.110	0.201	0.239	0.072	0.160
	(1.692)	(1.527)	(2.115)	(1.866)	(2.218)	(1.438)	(1.897)	(1.723)	(1.151)	(1.044)	(0.845)	(0.815)	(0.301)	(0.410)	(0.736)	(0.965)	(0.163)	(0.449)
$SC_{i,t/t-1}$		0.614***		0.591***		0.529**		0.404**		0.605***		0.499**		0.271		0.256		0.476**
		(2.827)		(2.735)		(2.296)		(2.258)		(2.753)		(2.561)		(1.397)		(1.197)		(2.049)
Skills																		
$Agghigh_{i,t-1}$			0.665	0.374														
			(0.534)	(0.348)														
$\Delta Agghigh_{i,t-1}$			0.563	0.449														
			(0.739)	(0.529)														
$Agg.low_{i,t-1}$					−0.032	−0.313												
					(−0.030)	(−0.388)												
$\Delta Agglow_{i,t-1}$					−1.447*	−0.986												
					(−1.730)	(−1.225)												
Innovation																		
$Sc.based_{i,t-1}$									5.825*	5.611**								
									(1.912)	(2.079)								
$\Delta\ Sc.based_{i,t-1}$									2.395	2.839								
									(0.699)	(1.077)								
$Sp.supp_{i,t-1}$											7.232***	5.071**						
											(2.712)	(2.337)						
$\Delta\ Sp.supp_{i,t-1}$											1.585	0.722						
											(1.588)	(1.020)						
$Sup.domin_{i,t-1}$							0.351	0.150										
							(0.505)	(0.272)										
$\Delta Sup.domin_{i,t-1}$							−1.224*	−0.740										
							(−1.654)	(−1.395)										

(continued)

Table 13 Continued

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
ICT																		
$ICTPM_{i,t-1}$													10.003***	9.070***	12.561***	10.927***		
													(3.431)	(2.702)	(3.810)	(3.850)		
$\Delta ICTPM_{i,t-1}$													5.699***	5.297***	7.491***	6.634***		
													(4.617)	(3.367)	(5.847)	(3.585)		
$ICTPS_{i,t-1}$													−4.547	−2.421			−10.227**	−5.692*
													(−1.563)	(−0.811)			(−2.056)	(−1.792)
$\Delta ICTPS_{i,t-1}$													1.795	1.739			0.006	1.020
													(1.521)	(1.347)			(0.002)	(0.363)
$ICTUM_{i,t-1}$															−1.999*	−1.962*		
															(−1.684)	(−1.893)		
$\Delta ICTUM_{i,t-1}$															−3.145*	−2.836*		
															(−1.93)	(−1.942)		
$ICTUS_{i,t-1}$																	0.391	0.500
																	(0.542)	(0.870)
$\Delta ICTUS_{i,t-1}$																	−0.386	−0.613
																	(−0.665)	(−1.011)
No. of observations	187	187	187	187	187	187	187	187	187	187	187	187	187	187	187	187	187	187
No. of countries	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
m_2	−0.401	−0.266	−0.336	−0.271	−0.349	−0.279	−0.300	−0.254	−0.233	−0.218	−0.339	−0.279	−0.221	−0.225	−0.239	−0.230	−0.325	−0.341

***, **, *Statistically significant at 1%, 5%, and 10%.

Notes: (i) Time dummies are included in all equations; (ii) asymptotic standard errors robust to general cross-section and time series heteroskedasticity are reported in parentheses; (iii) GMM estimates are all one step; (iv) lagged values of the dependent variable and the explanatory variables are used as instruments.

The pace at which structural change takes place, proxied by the Nickell index (*SC*), is one of the more robust explanatory variables. *Ceteris paribus*, an increase in the Nickell index in 1 percentage point results, on average, in additional annual productivity growth of 0.31 percentage points in 1 year lag regressions, and of about 0.11 percentage points in 5 year lag regressions.[32]

Many of the variables used to reflect the direction of structural change according to the selected technological and skill industry categories also show great robustness, although in some cases their significance tends to decrease with the inclusion of the *SC* variable. The coefficients for the skill variables, in particular, present the expected signs and are in most cases statistically significant. According to our findings, an increase in the share of high-skill industries results in a productivity growth bonus, whereas the opposite occurs with respect to low-skill industries.

The science-based share variable also emerges as strongly robust. Its positive impact is particularly high when considering 5-year lags and employment-based estimations [cf. regressions (9) and (10) in Tables 10–13]. More precisely, a difference of 1 percentage point in the science-based share gives a difference of about 0.4 percentage points in the annual productivity growth rate when value added data are used, and about 1.1 percentage points when using employment data.

Robust results are also found regarding both specialized suppliers and supplier-dominated variables. As expected, the latter show a negative influence on productivity growth, which is significant in value-added equations (share variable), and in employment-based regressions (changes in the share variable). The coefficients for the specialized suppliers variables, on the other hand, turn out significant and with the expected signs when 5-year lags are considered, although they emerge as non-significant when shorter lags are used instead.

With regard to the influence of ICT industries over productivity growth, the results point to a decisive role of ICT producing manufacturing (ICTPM) industries. The coefficient regarding the lagged share of this variable is positive and strongly significant in most equations. Also noticeable is that the impact of the ICTPM share is quite strong, particularly when employment data are considered. More precisely, an increase in the share of ICTPM industries by 1 percentage point amounts to a more than 1 percentage point increase in the annual productivity growth rate (cf. Tables 11–13). ICT producing services (ICTPS) industries, on the other hand, emerge as less relevant. The coefficient of the variation in the share of these industries has always the expected positive sign, but has only a significant impact over productivity growth in two of the regressions estimated. Furthermore, the coefficient for the lagged share presents a negative sign in many occasions, which is significant in some of the estimations considering employment data. This seemingly counter-intuitive result may reflect the rather low shares in these industries in

[32]Cf. Table A3 in the Appendix A.

some of the fastest growing countries in our sample (e.g. Korea and Taiwan) during the whole period under study. The coefficients regarding ICT-using industries are in general non-significant, and when significant, show a negative sign.

Looking globally at the results on the selected industry groups variables, it can be seen furthermore that their influence over productivity growth stems mostly from the share variables and not from the changes in the shares. The coefficients on the changes in the shares are only significant in four of the industry groups considered, and in these cases they tend to reinforce the impact of the corresponding industry group shares. It seems therefore that the pace at which global structural transformation takes place is important for rapid growth, as suggested by the evidence found with respect to the *SC* variable, but not so much the rate of change occurring in specific industry groups.

The positive effect of skills and technology-intensive industries on productivity growth, controlling for the influence of other variables that might also influence growth, and particularly its strong impact, gives empirical support to our assumption according to which substantial benefits have accrued to countries that successfully changed their structure towards more technologically advanced industries. Moreover, the fact that ICTPM industries have a strong impact on productivity growth seems to be in global agreement with the conceptualizations of the techno-economic paradigm developed within the neo-Schumpeterian streams of research (cf. Section 2). It is important to stress, however, that the results lend support to the view that ICT-related industries are strategic branches of economic activity, but only when *producing industries* (in the present case, producing manufacturing industries) are considered. This underlines the fact that most spillovers from advanced industries, and particularly ICT-producing industries are *local* and national in character, and therefore that "buying" is not the same as "producing". Hence, our results may be seen as reinforcing previous empirical evidence indicating that the gains from the diffusion of new technologies are especially relevant in economies which produce these technologies (e.g., Jaffe *et al.*, 1993; Maurseth and Verspagen, 1999; Jaffe and Trajtenberg, 2002).

We now explore further the relevance of ICTPM industries, considering separately the impact of each single industry included in this group under the modeling framework expressed in equation (1). Tables 14 and 15 show the results.

The results are similar to our previous findings regarding the pace of global structural change (*SC*) and the set of control variables (cf. Tables 14 and 15 and summary results in Table A3). The pace of structural transformation is again always positive and statistically significant, and the coefficient figures are very similar. The convergence effect is once again present, showing a faster speed of convergence in 1-year lag regressions.

The results obtained from the specific structural change variables show once more that their influence over productivity growth stems mostly from the share variables. When significant, the changes in the shares reinforce the impact of the corresponding

Table 14 The effect of structural change on productivity growth—impact of ICTPM industries (1-period lag, GMM estimates, all variables in first differences)

Variable	GVA						Hours					
	1	2	3	4	5	6	1	2	3	4	5	6
$Y_{i,t-1}$	0.951***	0.973***	0.972***	0.963***	0.910***	0.955***	0.930***	0.957***	0.972***	0.963***	0.928***	0.931***
	(35.243)	(56.221)	(57.905)	(53.501)	(23.826)	(43.900)	(32.529)	(41.736)	(59.099)	(50.603)	(28.476)	(32.230)
$EDUC_{i,t-1}$	0.017*	0.014*	−0.005	0.015*	0.013	0.020**	0.021**	0.013*	-0.005	0.018**	0.020	0.015
	(1.835)	(1.409)	(−1.070)	(1.677)	(0.771)	(2.191)	(2.497)	(1.725)	(-0.981)	(2.116)	(1.091)	(1.450)
$\Delta EDUC_{i,t-1}$	−0.043	−0.047	0.003	−0.044	−0.008	−0.047	−0.057	−0.050	−0.010	−0.049	−0.051	−0.055
	(−0.879)	(−0.899)	(0.091)	(−0.867)	(−0.180)	(−0.960)	(−1.262)	(−1.056)	(−0.346)	(−0.944)	(−1.029)	(−1.241)
$INV_{i,t-1}$	−0.223***	−0.161**	−0.017	−0.216**	−0.159	−0.195**	−0.238***	−0.143	0.016	−0.222**	−0.195	−0.169*
	(−2.668)	(−2.189)	(−0.483)	(−2.404)	(−1.552)	(−2.122)	(−2.732)	(−1.904)	(0.312)	(−2.253)	(−1.598)	(−1.774)
$\Delta INV_{i,t-1}$	0.454***	0.370***	0.336***	0.458***	0.420***	0.455***	0.392***	0.323***	0.317***	0.473***	0.463***	0.354***
	(3.442)	(3.089)	(3.110)	(4.189)	(3.802)	(3.652)	(3.982)	(2.792)	(3.144)	(3.705)	(3.089)	(3.350)
$SC_{i,t/t-1}$	0.279**	0.294*	0.357***	0.310**	0.370***	0.355***	0.331**	0.267*	0.402***	0.323***	0.259**	0.268*
	(2.276)	(1.977)	(5.234)	(2.524)	(3.585)	(3.416)	(1.865)	(1.771)	(6.692)	(2.663)	(2.504)	(1.951)
ICTPM industries												
$ISIC\ 30_{i,t-1}$	2.087***						4.542***					
	(2.742)						(3.012)					
$\Delta ISIC\ 30_{i,t-1}$	−0.009						0.009					
	(−0.261)						(1.805)					
$ISIC\ 313_{i,t-1}$		0.690						1.525*				
		(1.076)						(1.723)				
$\Delta ISIC\ 313_{i,t-1}$		−0.010						−1.576				
		(−1.485)						(−0.979)				
$ISIC\ 321_{i,t-1}$			1.078						1.827**			
			(1.549)						(2.190)			
$\Delta ISIC\ 321_{i,t-1}$			0.105						3.352**			
			(0.169)						(2.331)			

(continued)

Table 14 Continued

Variable	GVA						Hours					
	1	2	3	4	5	6	1	2	3	4	5	6
ISIC $322_{i,t-1}$				−0.203						−0.798		
				(−0.443)						(−0.439)		
Δ*ISIC* $322_{i,t-1}$				−0.870**						−0.776		
				(−2.172)						(−0.276)		
ISIC $323_{i,t-1}$					−4.913***						−2.480	
					(−2.837)						(−1.427)	
Δ*ISIC* $323_{i,t-1}$					1.840						3.963	
					(0.755)						(1.094)	
ISIC $331_{i,t-1}$						1.756						1.241**
						(0.898)						(2.272)
Δ*ISIC* $331_{i,t-1}$						−0.021						−2.546**
						(−1.175)						(−1.996)
No. of observations	217	217	217	217	217	217	217	217	217	217	217	217
No. of countries	10	10	10	10	10	10	10	10	10	10	10	10
m_2	−0.394	−0.408	−0.402	−0.398	−0.401	−0.406	−0.403	−0.399	−0.401	−0.402	−0.410	−0.383

***, **, *Statistically significant at 1%, 5%, and 10%.

Notes: (i) Time dummies are included in all equations; (ii) asymptotic standard errors robust to general cross-section and time series heteroskedasticity are reported in parentheses; (iii) GMM estimates are all one step; (iv) lagged values of the dependent variable and the explanatory variables are used as instruments.

Table 15 The effect of structural change on productivity growth—impact of ICTPM industries (5-period lag, GMM estimates, all variables in first differences)

Variable	GVA						Hours					
	1	2	3	4	5	6	1	2	3	4	5	6
$Y_{i,t-1}$	0.933***	0.995***	0.731***	0.925***	0.943***	0.870***	0.693***	0.992***	0.740***	0.906***	0.947***	0.855***
	(9.718)	(14.594)	(4.488)	(10.982)	(10.678)	(5.960)	(6.893)	(12.331)	(6.475)	(8.628)	(11.140)	(5.760)
$EDUC_{i,t-1}$	−0.043	−0.030	−0.059	−0.042	−0.060	−0.031	0.001	−0.044	−0.057	−0.054	−0.049	−0.036
	(−1.091)	(−0.789)	(−1.665)	(−1.022)	(−1.424)	(−0.848)	(0.020)	(−1.385)	(−1.377)	(−1.299)	(−1.257)	(−0.998)
$\Delta EDUC_{i,t-1}$	−0.030	−0.038	−0.023	−0.074	−0.030	−0.025	−0.060	−0.037	−0.067	−0.066	−0.039	−0.064
	(−0.520)	(−0.698)	(−0.501)	(−1.243)	(−0.506)	(−0.536)	(−1.117)	(−0.705)	(−1.253)	(−0.998)	(−0.653)	(−1.300)
$INV_{i,t-1}$	0.361	0.239	0.270	0.285	0.466	0.481	−0.063	0.278	0.462	0.427	0.609	0.198
	(0.762)	(0.624)	(0.805)	(0.754)	(1.124)	(1.381)	(−0.164)	(0.684)	(1.178)	(0.895)	(1.357)	(0.530)
$\Delta INV_{i,t-1}$	0.400	0.259	0.440**	0.435*	0.578*	0.448*	0.103	0.378	0.495	0.424	0.661**	0.302
	(1.378)	(0.831)	(2.007)	(1.633)	(1.801)	(1.990)	(0.353)	(1.163)	(1.533)	(1.269)	(2.079)	(1.232)
$SC_{i,t/t-1}$	0.576***	0.596**	0.505***	0.648***	0.598***	0.453**	0.497**	0.590***	0.518**	0.594***	0.588***	0.331**
	(2.795)	(2.280)	(3.223)	(3.191)	(2.828)	(2.515)	(2.409)	(2.830)	(2.428)	(2.924)	(2.731)	(2.083)
ICTPM industries												
$ISIC\ 30_{i,t-1}$	5.462**						23.268***					
	(2.201)						(4.485)					
$\Delta ISIC\ 30_{i,t-1}$	−0.004						−1.006					
	(−0.519)						(−0.239)					
$ISIC\ 313_{i,t-1}$		3.560						3.290				
		(1.339)						(1.052)				
$\Delta ISIC\ 313_{i,t-1}$		0.028						2.490**				
		1.166)						(2.108)				
$ISIC\ 321_{i,t-1}$			12.713**						18.491***			
			(2.145)						(2.715)			
$\Delta ISIC\ 321_{i,t-1}$			5.611***						8.517***			
			(3.439)						(3.281)			

(continued)

Table 15 Continued

Variable	GVA						Hours					
	1	2	3	4	5	6	1	2	3	4	5	6
ISIC $322_{i,t-1}$				3.334						9.836		
				(1.353)						(1.233)		
Δ*ISIC* $322_{i,t-1}$				−0.932						0.563		
				(−1.496)						(0.094)		
ISIC $323_{i,t-1}$					−3.363						−2.515	
					(−0.985)						(−0.761)	
Δ*ISIC* $323_{i,t-1}$					−0.569						2.664	
					(−0.105)						(0.629)	
ISIC $331_{i,t-1}$						3.873**						4.913***
						(2.102)						(2.675)
Δ*ISIC* $331_{i,t-1}$						2.474***						2.717
						(3.275)						(1.401)
No. of observations	187	187	187	187	187	187	187	187	187	187	187	187
No. of countries	10	10	10	10	10	10	10	10	10	10	10	10
m_2	−0.194	−0.211	−0.102	−0.257	−0.276	−0.255	−0.239	−0.226	−0.191	−0.253	−0.283	−0.263

***, **, *Statistically significant at 1%, 5%, and 10%.

Notes: (i) Time dummies are included in all equations; (ii) asymptotic standard errors robust to general cross-section and time series heteroskedasticity are reported in parentheses; (iii) GMM estimates are all one step; (iv) lagged values of the dependent variable and the explanatory variables are used as instruments.

industry group shares. More importantly, the evidence found shows that the industries included in the ICTPM group were not equally relevant in promoting labor productivity growth. Office machinery, electronic valves and tubes, and scientific instruments industries emerge as those with a decisive influence on productivity growth. The insulated wire industry is only statistically significant when employment data and 1-year lag regressions are considered. The telecommunication equipment and radio and television receivers industries, on the other hand, generally fail to be statistically significant. These results are in global agreement with the evidence depicted in Figure 2. The fastest growing countries from our sample present noticeable changes in the composition of the ICTPM industry group, which show precisely an increase in office machinery and electronic valves and tubes industries.

These results are to some extent at odds with the evidence found in Carree (2003), who found the Radio, TV and communications equipment industry as the only electronics industry with a positive and significant impact on productivity growth. Moreover, the average estimated impact of the specific branches of ICTPM industries in this study are, in general, much higher than in Carree's work.[33] Carree's results were, however, determined for a larger sample of OECD countries, which included developed as well as less developed countries. Apart from differences in the estimation procedure, this result may therefore reflect the fact that the influence of specifically oriented structural change in the ICTPM industries was more important in relatively less developed economies. Perez's contention (cf. Section 2) that relatively these economies could benefit more from structural changes towards industries related to new techno-economic paradigms in periods of transition seems, in this way, to get some confirmation.

6. Conclusion

This article explores the relationship between structural and technological change and economic growth, taking into account a number of relatively less developed countries in the late 1970s. According to neo-Schumpeterian notions, there are reasons to expect technologically leading industries, and particularly those more closely related to new technological paradigms, to have a major influence on growth. Moreover, according to some of the views expressed (e.g. Perez, 1985), it is precisely in periods of transition and emergence of new techno-economic paradigms that the relatively less developed countries have greater opportunities to catch-up.

[33]The estimated coefficient of the only statistical significant industry in Carree's work (from Radio, TV and communications equipment) suggests that a 1% higher share of this industry has almost 0.2% higher productivity growth per annum. Our corresponding figure, although not significant, is 2% per annum [cf. regression (4) in Table 15].

Using a simple descriptive analysis we show that rapid growth experiences during the 1979–2003 period in the countries in our sample were intimately connected with strong structural change, measured by the computation of Nickell and Lilien indices. Furthermore, the countries with faster structural change were also the ones experiencing more profound increases in the relative importance of skills and innovation-intensive industries, and the largest decreases in low-skill and supplier-dominated industries. These results suggest that an explanation for the widely different growth patterns observed between 1979 and 2003 for the selected countries might reside in their differing ability to promote changes in the economic structure towards more skilled and innovation-intensive activities.

This assumption was examined in the last part of the article, through the estimation of dynamic panel data regressions. According to our findings, the high-skill, science-based industries have a positive and significant impact on productivity growth, above the influence of physical capital renewal rate and, in the case of science-based and ICTPM industries, of the "global" pace of structural change. The results thus provide empirical support to the assumption that substantial benefits have accrued to countries that successfully assigned larger amounts of resources to more technologically advanced industries, namely science-based and ICT-producing manufacturing industries.

At the same time, our results lend strong support to the view that ICT-related industries are strategic branches of economic activity, but only when *producing industries* are considered. This underlines the fact that most spillovers from advanced industries, and particularly ICT producing industries are *local* and national in character, and therefore that "buying" is not the same as "producing". Contrarily to the conclusions presented in other studies (e.g. Barros, 2002), we therefore argue that the implementation of industrial policies aimed at changing the pattern of specialization towards the promotion of leading technology sectors may pay-off. [34]

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[34]Not necessarily ICT industries, since leading technologies change over time (Fagerberg, 2000).

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Appendix A

Table A1 Industry shares in total hours worked (%) (1979, various countries)

	Skill categories			Innovation categories						ICT categories						
	Aggregate low[a]	Medium	Aggregate high[b]	Supplier-dominated	Scale-intensive	Specialized supplier	Science-based	Information-intensive	Non-market services	ICTPM	ICTPS	ICTUM	ICTUS	NICTM	NICTS	NICTO
Australia	49.9	18.7	31.4	30.6	13.4	5.4	1.5	33.0	16.0	1.0	2.1	6.3	22.6	13.6	35.5	18.9
Austria	59.7	14.9	25.5	42.8	11.7	6.5	1.9	22.6	14.6	1.5	1.9	7.6	14.7	15.3	29.8	29.1
Belgium	43.7	18.1	38.2	24.2	13.9	6.5	3.6	29.5	22.3	1.4	3.3	7.1	19.7	17.2	39.2	12.2
Canada	46.8	16.9	36.3	31.5	11.1	6.9	1.7	30.2	18.6	1.1	3.1	6.1	21.2	13.2	39.6	15.7
Denmark	45.2	16.8	38.0	28.7	9.2	7.7	1.7	28.5	24.2	1.1	2.4	8.2	19.7	11.2	40.6	16.9
Finland	55.6	17.3	27.0	43.2	8.6	5.6	1.4	23.5	17.6	0.7	1.9	8.8	14.8	13.2	32.4	28.2
France	49.1	15.8	35.1	33.7	11.5	8.2	1.8	25.7	19.0	1.4	2.7	8.1	17.3	14.4	35.6	20.6
Germany	44.8	21.6	33.7	28.4	14.5	10.1	4.0	24.3	18.6	2.0	2.5	10.9	17.8	17.7	32.8	16.3
Greece	72.4	9.7	18.0	55.6	9.8	3.3	0.9	20.6	9.9	0.2	1.5	8.1	12.0	12.4	27.4	38.3
Ireland	57.3	14.2	28.5	42.7	13.0	5.1	1.9	21.2	16.0	1.2	3.5	6.5	14.3	15.1	30.6	28.7
Italy	58.0	15.3	26.8	40.4	11.8	6.9	2.7	22.3	16.0	1.3	1.8	9.6	15.6	18.5	30.3	23.0
Japan	61.1	15.5	23.4	45.7	8.5	7.0	2.4	29.1	7.3	1.8	1.7	8.7	21.9	11.9	28.6	25.5
Korea	74.0	11.5	14.4	59.7	7.8	4.2	2.3	19.6	6.3	2.3	0.6	5.7	13.6	16.4	20.3	41.1
The Netherlands	43.4	15.5	41.0	31.3	10.0	6.1	3.2	27.7	21.7	2.2	1.7	8.7	19.2	12.1	40.1	16.0
Norway	47.8	16.9	35.3	31.4	11.1	5.0	1.7	28.2	22.6	0.8	2.3	7.8	17.1	11.5	39.4	21.1
Portugal	66.6	10.1	23.3	54.4	9.6	2.4	1.6	19.9	12.1	0.7	1.0	5.3	13.7	18.4	26.8	34.1
Spain	67.8	10.6	21.5	46.3	11.0	3.9	2.0	23.7	13.1	0.7	1.1	6.7	15.4	15.4	31.6	29.1
Sweden	40.2	19.3	40.5	29.2	10.5	8.0	1.8	24.8	25.9	1.8	2.9	7.8	16.8	13.3	42.6	14.9
Taiwan	66.8	13.4	19.8	47.7	9.4	8.2	4.7	21.5	8.4	4.1	0.6	9.8	15.7	19.6	20.9	29.4
UK	45.5	18.8	35.7	27.3	15.5	8.8	2.9	27.8	17.7	1.9	2.6	9.1	19.2	16.8	36.1	14.3
United States	39.2	18.0	42.8	25.6	10.7	8.5	1.9	29.0	24.3	2.2	2.5	7.7	20.4	12.6	44.1	10.5
Average	54.0	15.7	30.3	38.1	11.1	6.4	2.3	25.4	16.8	1.5	2.1	7.8	17.3	14.7	33.5	23.0
Std. Dev.	10.9	3.2	8.2	10.6	2.1	2.0	0.9	3.9	5.7	0.8	0.8	1.4	3.0	2.6	6.7	8.6
Maximum	74.0	21.6	42.8	59.7	15.5	10.1	4.7	33.0	25.9	4.1	3.5	10.9	22.6	19.6	44.1	41.1
Minimum	39.2	9.7	14.4	24.2	7.8	2.4	0.9	19.6	6.3	0.2	0.6	5.3	12.0	11.2	20.3	10.5

[a]Includes very low, low, and medium-low skill industries.

[b]Includes medium-high, high, and very high skill industries.

[c]Year of reference: 1980.

Source: GGDC—60 Industry Database.

(N)ICT[P/U]{M/S/O}: (non) information and communication technology [producer/user]{manufacturing/services/other} industries.

Table A2 Average years of education of the working age population, 1979–2003

	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
Austria	10.3	10.4	10.5	10.6	10.7	10.8	10.9	10.9	11.0	11.1	11.2	11.3	11.3	11.4	11.4	11.4	11.5	11.6	11.7	11.8	11.9	12.1	12.1	12.2	12.2
Finland	9.5	9.6	9.7	9.7	9.8	9.9	10.0	10.1	10.1	10.2	10.3	10.4	10.5	10.6	10.7	10.8	10.9	11.0	11.1	11.2	11.5	11.8	12.1	12.4	12.5
Greece	7.9	7.9	8.0	8.1	8.2	8.2	8.3	8.4	8.5	8.6	8.7	8.8	9.0	9.1	9.2	9.3	9.5	9.6	9.7	9.9	10.2	10.2	10.3	10.4	10.4
Ireland	8.4	8.5	8.6	8.7	8.8	8.9	9.0	9.0	9.1	9.2	9.3	9.4	9.5	9.6	9.7	9.8	10.0	10.1	10.2	10.3	10.5	10.6	10.8	10.9	10.9
Italy	7.3	7.3	7.4	7.5	7.6	7.7	7.8	7.9	8.0	8.1	8.2	8.4	8.5	8.6	8.8	9.0	9.2	9.4	9.6	9.8	10.0	10.1	10.2	10.4	10.4
Japan	10.1	10.2	10.3	10.4	10.5	10.6	10.7	10.8	10.9	11.0	11.1	11.2	11.4	11.5	11.6	11.7	11.9	12.0	12.1	12.3	12.3	12.4	12.5	12.7	12.7
Korea	6.8	6.8	7.0	7.3	7.5	7.8	8.0	8.3	8.5	8.7	9.0	9.3	9.4	9.6	9.7	9.9	10.1	10.2	10.2	10.3	10.4	10.5	10.5	10.6	10.8
Portugal	6.9	6.9	6.9	7.0	7.0	7.0	7.1	7.1	7.1	7.2	7.2	7.2	7.3	7.3	7.4	7.5	7.5	7.6	7.7	7.7	7.8	7.8	7.8	7.8	8.0
Spain	6.3	6.3	6.4	6.5	6.6	6.7	6.8	6.9	7.0	7.1	7.2	7.3	7.5	7.6	7.8	7.9	8.1	8.3	8.5	8.7	9.1	9.3	9.5	9.6	9.7
Taiwan	6.4	6.4	6.5	6.6	6.7	6.8	6.9	7.0	7.1	7.2	7.3	7.4	7.6	7.7	7.8	7.9	8.0	8.1	8.2	8.3	8.4	8.5	8.6	8.7	8.8

Notes: Data for the 1979–1998 period regarding all countries, except Korea and Taiwan, is from Bassanini and Scarpetta (2001). We extend Bassanini and Scarpetta's estimates up to 2003, considering data on educational attainment from OECD *Education at a Glance* (various issues), and using the cumulative years of schooling by educational level considered by the authors.

Data on Korea and Taiwan between 1980 and 2000 are based on Barro and Lee (2001). We interpolate the 5-year observations provided by the authors to obtain annual figures for both countries. Education estimates for Korea between 2001 and 2003 are obtained considering data on educational attainment from OECD *Education at a Glance*, and assuming the cumulative years of schooling used by Barro and Lee (2001). Finally, estimates regarding Taiwan for the years 2001–2003 are obtained assuming that the average years of education of the working age population during this period has grown at an annual rate similar to the one experienced in the previous quinquennium.

Table A3 Regressions Summary (average estimates for the statistically significant coefficients)

	GVA (lag 1) (Table 10)	Hours (lag 1) (Table 11)	Per year estimates[a]	
			GVA (lag 5) (Table 12)	Hours (lag 5) (Table 13)
Convergence rate	+0.041	+0.049	+0.024	+0.014
	[0.046]	[0.053]	[0.020]	[0.029]
Conditioning variables				
EDUC	+0.018 (11/18)	+0.019 (6/18)	0	0
	[0.017 (3/6)	[0.017 (3/6)]	0	0
V_EDUC	0	0	0	−0.018 (2/18)
	0	0	0	0
INV	−0.219 (11/18)	−0.210 (8/18)	+0.147 (2/18)	0
	[−0.199 (4/6)]	[−0.210 (3/6)]	0	0
V_INV	+0.399	+0.369 (17/18)	+0.108 (9/18)	+0.110 (6/18)
	[0.416]	[0.387]	[+0.095 (4/6)]	[+0.132 (1/6)]
NICKELL	+0.304 (7/9)	+0.323	+0.109 (8/9)	+0.106 (7/9)
	[+0.328]	[+0.308]	[+0.113]	[+0.104]
Skills taxonomy				
AggHig	+0.719	+0.389	+0.324	0
V_AggHigh	0	0	0	0
Agglow	−0.536	0	−0.404	0
V_Agglow	0	0	0	−0.283
Innovation taxonomy				
SB	+0.404	0	+0.465	+1.144
V_SB	0	0	+0.429	0
SS	0	0	+0.553	+1.230
V_SS	0	0	0	0
SD	−0.767	0	−0.299	0
V_SD	0	−0.594	0	−0.245
ICT taxonomy				
ICTPM	0	+1.309	+1.132	+2.115
V_ICPM	+0.904	0	0	+1.256
ICTPS	0	−1.636	0	−1.592
V_ICTPS	0	0	+0.679	0
ICTUM	0	−0.524	0	−0.396
V_ICTUM	0	0	0	−0.598
ICTUS	−0.397	0	0	0
V_ICTUS	0	0	0	0
ICTPM				
Office machinery and computers				
ISIC30	+2.087	+4.542	+1.092	+4.654
V_ ISIC30	0	+0.009	0	0

(continued)

Table A3 Continued

	GVA (lag 1) (Table 10)	Hours (lag 1) (Table 11)	Per year estimates[a]	
			GVA (lag 5) (Table 12)	Hours (lag 5) (Table 13)
Insulated wire				
ISIC313	0	+1.525	0	0
V_ISIC313	0	0	0	+0.498
Electronic valves and tubes				
ISIC321	0	+1.827	+2.543	+3.698
V_ISIC321	0	+3.352	+1.122	+1.703
Telecommunication equipment				
ISIC322	0	0	0	0
V_ISIC322	−0.870	0	0	0
Radio and television receivers				
ISIC323	−4.913	0	0	0
V_ISIC323	0	0	0	0
Scientific instruments				
ISIC331	0	+1.241	+0.746	+0.983
V_ISIC331	0	−2.545	+0.495	0

[a]Obtained simply by dividing the average estimated coefficients in Tables 12 and 13 by five (number of periods considered in the lag). Figures in [] for ICTPM specifications (Tables 14 and 15); 0—statistically not significant; (*x/y*) means the number (*x*) of econometric specifications in total specification (*y*) estimated for which the variable achieved a statistically significant estimate; when (*x/y*) is absent it means that all the corresponding estimates were statiscally significant.