

TECHNOLOGICAL SPECIALIZATION, TECHNOLOGICAL CONVERGENCE AND GROWTH

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Resumo

Este trabalho tem como objetivo estudar o papel das ‘boas’ especializações tecnológicas na evolução da convergência tecnológica e do crescimento. Para isso, o artigo usa medidas de especialização smithiana e ricardiana, diferenciando neste caso entre medidas dinâmicas (baseadas no crescimento da quota de patentes por tecnologia) e estáticas (baseada na intensidade em P&D setorial). A partir de dados do Escritório Europeu de Patentes entre 1980 e 2010, o artigo mostra que houve convergência tecnológica agregada e desagregada para um conjunto selecionado de 34 países, mas apenas a especialização smithiana se associa significativamente com convergência. O artigo também estima o papel das variáveis de especialização tecnológica no crescimento usando um modelo estendido de crescimento endógeno para uma amostra de 22 países. Os resultados empíricos confirmam que a especialização tecnológica importa, mas com diferentes interpretações para medidas estáticas e dinâmicas acerca da qualificação da “bondade” de dita especialização.

Abstract

This paper aims to study the role of ‘good’ technological specializations in the evolution of technological convergence and growth. For that, the paper uses the ricardian and smithian specialization and differentiates one dynamic (based in the growth of patents share by technology) and one static (based on R&D intensity by sectors) criterions for measuring ricardian specialization. Using patent data from European Patent Office between 1980 and 2010, the paper show that there was aggregate and desegregate technological convergence for 34 selected countries, but just smithian specialization is associated significantly with convergence. The paper also estimates the role of the technological specialization variables for growth using an extended model of endogenous growth for a sample of 22 countries. Empirical results confirms that ‘specialization matters’, but with different interpretation for static and dynamic measures of *goodness* for technological specialization.

Keywords: Technological specialization, convergence, catching-up, growth.

Palavras-chave: Especialização tecnológica, convergência, captura tecnológica, crescimento.

JEL Clasificação: O33, O47.

Área 5 - Crescimento, Desenvolvimento Econômico e Instituições.

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INTRODUCTION

Convergence analysis allows to observe the evolution of differences of growth among countries and along time. To convergence occurs, less developed countries must get a rhythm of growth higher than the more developed ones. Literature offers different approaches to develop a theory of economic convergence to identify the conditions that ensure it. From the neoclassical approach (with exogenous technical progress), poorest regions should have more potential for growth because of the decreasing returns of capital in the richest ones. Endogenous growth models, even assuming endogenous technical change, also emphasizes in the role of capital accumulation as the main explicative factor for long term growth and convergence.

A second approach comes from the theory of technology gaps (Maurseth, 2001). Differences in the levels of technological advance could not maintain too long due to knowledge and technical change spillovers. Considering the public character of knowledge, delayed countries could be able to achieve higher speed of technological advance by the absorption of those spillovers. If delayed countries still perform several effort to develop domestic absorptive capacity (in the Cohen and Levinthal sense), the absorption become a real catch up process and convergence between delayers and leaders accelerates. Technology transfer also stimulates convergence through productivity growth and its effect should be stronger for countries that are more distant from the technological frontier (Camerona et al, 2005). However, for some authors, technological progress can cause simultaneously convergence and divergence; convergence for regions that adopt technologies with lower costs of industrial equipment and divergence between that regions and the rest of the world (Sadik, 2008). This is the reason because Camerona et al, (2005) found that countries that fail to converge to the world technological frontier are not the richest anymore, but the poorest.

Other elements can play a major role on economic convergence like transportation costs, the access to markets or the proximity to areas of high industrial concentration. From the new economic geography, the interaction between regions –more than individual characteristics of regions- acquires an important dimension in the convergence analysis. For example, the extent in which technological spillovers can be taken is directly related to the geographical distance.

Under economic integration, the expected results of those models change (Molle and Boekhout, 1995; Maurseth, 2001; Gonca and Keller, 2003; Camerona *et al.*, 1995; Sadik, 2008). Usually, globalization is linked to convergence and de-globalization is linked to divergence (Williamson, 1996). For neoclassical scholars, international trade should drive to *factor price equalization* and, as a consequence, decreasing returns of capital only happened in less capital-intensive regions (*see* Maurseth, 2001). For endogenous growth theories, international trade provides access to new and higher markets as well as the reduction of the barriers to inputs flows (labor, capital and technology) allows the access to a larger base of knowledge. As growth is conducted by the labor force in R&D and the stocks of cumulated knowledge, economic integration should stimulate growth, but not necessary convergence (Romer, 1990).

Nevertheless, it is not clear the way through which the technology transfer is transmitted in opened economies. There are some doubts about the role of international trade when compared to the role of national efforts to develop absorptive capacity. Camerona *et al.* (2005) found for United Kingdom that there is a positive relationship between international trade and productivity growth. But when it is controlled the direct effect of human capital on productivity, the evidence about the effect of externalities as sources of productivity growth disappears. For economic geography, economic integration can result in both, convergence or divergence, and proximity configures a crucial role for technological spillovers. The

historical pattern for the European Union showed that economic integration brought a decrease of disparities since the SWW, but this tendency could reverse depending on the policies taken to stimulate mobilization of capital (Molle and Boekhout, 1995). More recent studies, also for Europe, pointed out that catch up and spillovers is more probable from neighbors than from rich countries (Maurseth, 2001).

For other authors, the main determinant for income convergence is the international technology diffusion of codified knowledge by active (learning) and passive (international trade and FDI) spillovers, which are closely related (Gonka and Keller, 2003). As more important the non-codified knowledge is, more centralized the creation and diffusion of technology will be. In that authors's view, the main cause of productivity differences is the *actually employed technological knowledge* as a consequence of the different propensities to adopt frontier technology knowledge. The huge empirical literature that they revised showed that, no matter which the approach was, foreign technological activity contribute positively to domestic productivity and its contribution is inversely correlated with economic size and level of development.

Another factor that has been considered recently in convergence studies is technological specialization. Based on the Kaldorian idea that 'specialization matters'¹, Jungmittag (2004) called attention on the role played by Ricardian specialization on 'good' technologies, this is, technologies with high technological opportunities. Good specialization should induce to higher rates of productivity growth because of the positive spillovers that emerge from them and because those technologies are related to sectors with high income elasticity. For Jungmittag, 'good' specialization is referred to R&D intensive technologies, this is, to *leading edge technologies* (drugs and medicines, office and computing machinery, radio, TV and communication equipment, aircraft, guided missiles and space vehicles) and *high level technologies* (chemicals and drugs, non-electrical machinery, electrical machinery, motor vehicles, other transport equipment and professional goods). The author tested the effect and found that this kind of specialization contributed significantly on European Union growth, especially the specialization in leading edge industries (technologies) between 1969 and 1998 period. As a consequence, he recommended public policies to stimulate some structural change towards R&D-intensive industries as well as cross-border technology diffusion and knowledge spillovers.

In his work, the contribution of the specialization in R&D intensive technologies for convergence was always negative, and strongly negative in case of specialization in leading-edge technologies. That would mean that countries specialized in this kind of technologies must be closed to the technological frontier and the induced growth from 'good specializations' make de distances bigger between the richest and the poorest.

Those findings suggest further questions. By one side, technological opportunity is not static. The dynamism and opportunities offered by a set of technologies in a specific moment can be strongly reduced in the next one. On the contrary, technologies apparently stagnant can present high opportunities if they are crossed by the natural trajectories of new paradigms in connected technologies (for example applications for agricultural goods from biotechnology advances). Secondly, technological specialization reflects, in somehow, the knowledge base of the productive structure (Urraca, 2011). As a consequence, technological specialization of a country reveals the technological strengths linked to its comparative advantages. So, there is an apparent contradiction in recommending stimulating structural change towards activities that can have nothing to do with domestic comparative advantage or, moreover, towards technologies that have no connection with the productive base. And finally, given the dynamic character of technological opportunity, an induced structural change running behind the past trajectories of technical change can be a wrong strategy if the trajectories of technological change alter their directions.

By the other side, if technological specialization matters for growth and for convergence, some policy implications come out. Depending on how the pattern of technological specialization is associated to growth and convergence, the correct hierarchy about 'good' or 'bad' technological specializations can drive to different policies, for example to promote the development of technologies linked to national

¹ This is an extended idea which different theoretical approaches converge to. For a theoretical review see Dalum et al (1999).

advantages inside to develop new technical bases; to support activities to compete internationally in new markets or to improve the competitive advantage in the old ones.

Under all those considerations, this paper aims: i) to observe the evolution of aggregate and disaggregate technological convergence for 34 countries between 1985 and 2010; ii) to measure the role of technological specialization defined in dynamic and static terms to growth.

1. TECHNOLOGICAL SPECIALIZATION AND TECHNOLOGICAL CONVERGENCE.

The evolution of aggregate technological convergence will be analyzed by adapting the methodology introduced by Barro and Sala i Martín (1990, 1991) to test the convergence in economic growth; the *beta convergence* equation, σ -convergence and standard deviation of patents per-capita stocks. σ -convergence is calculated as the standard deviation of patents per capita of each considered country² divided by the mean of the group and the mean of the whole world. Results are showed in table 1. Absolute measure of convergence (standard deviation) show that divergence is increasing along time. Nevertheless, relative measures of convergence (σ -convergence) show that there is a clear path of technological aggregate convergence along time, both, in relation to the world and in relation to the selected countries.

Table 1. σ -convergence (growth of patents stock per-capita)

	7885	8690	9195	9600	0105	0610
Standard Deviation	270.7	537.8	800.6	1203.3	1729.7	1481.9
Mean	188.9	405.5	652.8	1056.7	1615.9	435.9
σ (whole world)	6.4	6.3	6.0	6.0	6.1	4.1
σ (selected countries)	4.1	3.7	3.5	3.5	3.5	2.3

Source: Patents data from Space Bulletin, EPO, 1978-2011. Population data from World Penn Data for 34 countries.

β -convergence is measured as the estimator by regress:

$$p_{pc}^t = \alpha - \beta \ln P_{pc}^0,$$

Where p_{pc}^t is the patents stock rate of growth for the 1985-2010 period and $\ln P_{pc}^0$ is the logarithm of the initial value of the patents per capita stocks (1985-1990 period).

According with t-value test and two-tail p-values, the variable $lpatent$ is significant for a 95% confidence and the regression yields an estimated convergence rate of 13% per period.

The aggregate convergence hides different specializations across technical fields between countries. So, aggregate convergence says nothing about the strengths and weakness of national technological competences (Arquibugi and Pianta, 1994). Nevertheless, it is important to have a look to disaggregate convergence for several reasons. Firstly, because specific patterns of technological specialization can be associated to the building of absorptive capacity in some technologies over others. In this sense, the technology gaps between nations can be related to the distances in specific technologies that define different technological trajectories in long term. Assuming that different paradigms and

² These countries are: Argentina, Australia, Austria, Belgium, Brazil, Canada, China, Denmark, Finland, France, Germany, Greece, Hong-Kong, Iceland, India, Ireland, Italy, Israel, Japan, Korea Republic, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Portugal, Singapore, South Africa, Russian Federation, Spain, Sweden, Switzerland, United Kingdom and United States.

trajectories have different impacts on productive activities, those differences can result in different paths of convergence and growth.

Table 2. β -convergence (growth of patents stock per-capita)

	c	<i>L</i> _{patent}
coefficient	.0492516	-.0130742
t	1.76	-2.48
P-value	0.087	0.019

Source: Patents from Space Bulletin, EPO, 1978-2011. Population from World Penn Tables for 34 countries

Secondly, in a internationalized world where barriers to flows of embodied and disembodied knowledge slow down, catching up can be more accelerated in some technologies over others which could affect to the international division of technological activity in two possible directions: one, reinforcing the national competitive advantages, focused new efforts over previous specializations; two, inducing to a mobility towards the taking of advantages from new technological opportunities, receiving the technological spillovers from efforts developed anywhere. Both possible trajectories have different implications in terms of growth and public policy. On one hand, as a result of the followed direction, countries can become more similar or more dissimilar in their technological specialization patterns. The technological aggregate convergence can be accompanied by a pattern of international competition (case of higher similarity) or by a pattern of international cooperation (case of increasing dissimilarity) (Archibugi and Pianta, 1994). If patterns become dissimilar, so growth can be and, as a consequence, also aggregate convergence (at least in technological terms).

Arquibugi and Pianta (1994) concluded for a group of OECE countries that, in the eighties, the convergence process slowed down due to persistency of national specializations in innovation. They also observed that, even considering the effect of cumulative capabilities on the persistence, countries moved over new technological classes taking advantage of technological opportunities. The observed aggregate convergence hide behind growing differences between countries that also become more specialized. Maurseth (2001) pointed out that, from eighties, convergence of growth in European countries gained speed between 1980 and 1994. Poorest regions converged to richest even with strong differences in terms of number of patents, geographic distance, technological specialization and spillovers received.

From mid-nineties to now, some important global phenomena happened. Firstly, along the two last decades, increasing levels of openness were achieved globally. Secondly, new polarizations emerged in the international arena characterized by the leading role of BRICs and the decline of Europe and United States after the financial crisis of 2007. And thirdly, new tigers, especially South Korea, emerged as examples of fast and successful catching up, widely supported by public policies.

In this work, it will be used as measure of disaggregated convergence the chi-squared, (χ^2), calculated as

$$\chi^2 = \sum_{i=1}^n \frac{(p_{ij} - p_{iL})^2}{p_{iL}}$$

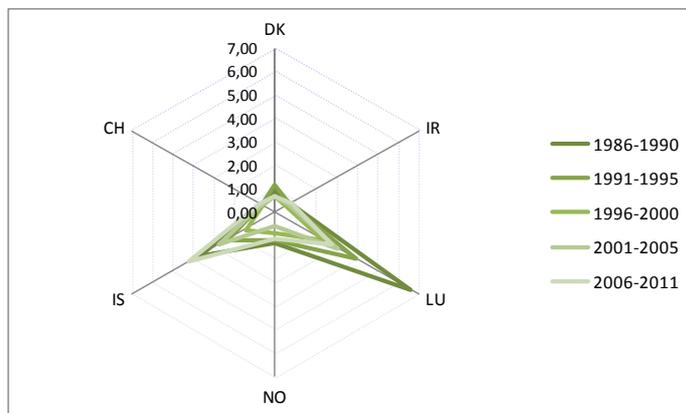
where p_{ij} is the j -country share or patents in i -technical field and p_{iL} is the share of

patents in the same technical field for the area of reference defined by leaders³ (United States, Japan and Germany). This indicator takes value 0, in the case of total similarity (convergence), and higher positive values as sectoral distributions become more dissimilar (divergence). Results are presented by groups of countries. Each group was defined according to the level of GDP per capita by mean between 2000 and 2008. Countries in Group 1 are characterized by being small and developed countries with a level of GDP per capita above 40,000 \$. In that group, there is a general trajectory to converge with leaders along the five considered periods. It is especially relevant the case of Luxembourg. Norway also follows a trend to converge until the 2001-2005 period. After that, it suddenly turns back its path towards divergence with a distance similar to that from initial period. The same effect is observed in Iceland, which inverted

³ These three countries take about 60% of total patents deposited in EPO between 1978 and 2010.

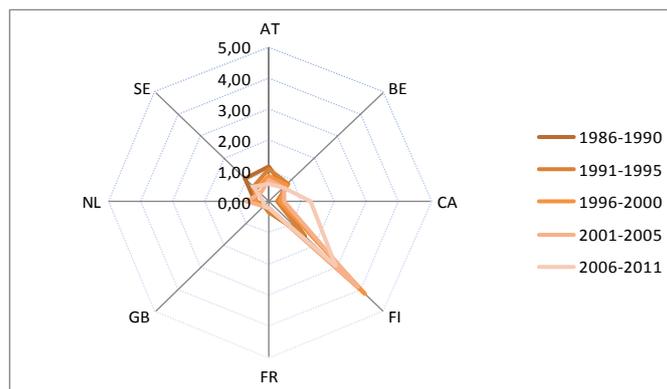
its trend from 1996-2000 period and achieved higher final distances with leaders than in the initial one. Denmark, Ireland and Switzerland show small modifications along time, keeping constant and small their distances with leaders (Figure 1).

Figure 1. Technological distance with leaders (χ^2). Group 1* : Denmark (DK), Ireland (IR), Luxembourg (LU), Norway (NO), Iceland (IS) and Switzerland (CH)



(*): Countries over 40,000 \$ per capita in PPP by mean between 2000-2008.

Figure 2. Technological distance with leaders (χ^2). Group 2* : Austria (AT), Belgium (BE), Canada (CA), Finland (FI), France (FR), Great Britain (GB), Netherlands (NL) and Sweden (SE)

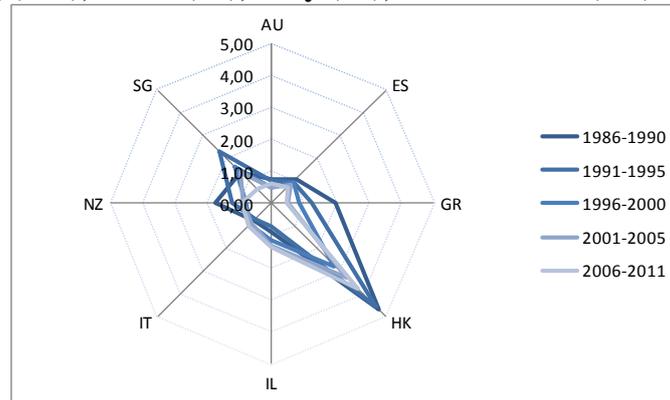


(*): Countries between 30,000 and 40,000 \$ per capita in PPP by mean between 2000-2008.

Group 2 take countries with GDP per capita between 30,000 and 40,000 \$. These are developed countries with a medium size in terms of population and an elevated level of GDP. The distances to leaders are really small for countries like France, Great Britain Belgium and Netherlands. This countries show a stability of their distances with leaders into a general trend to converge. Sweden and Austria, even starting with higher distances, trend also to converge. Nevertheless, Finland and Canada show a trend to divergence due to the path towards strong specializations in audio-visual, telecommunications and information technologies.

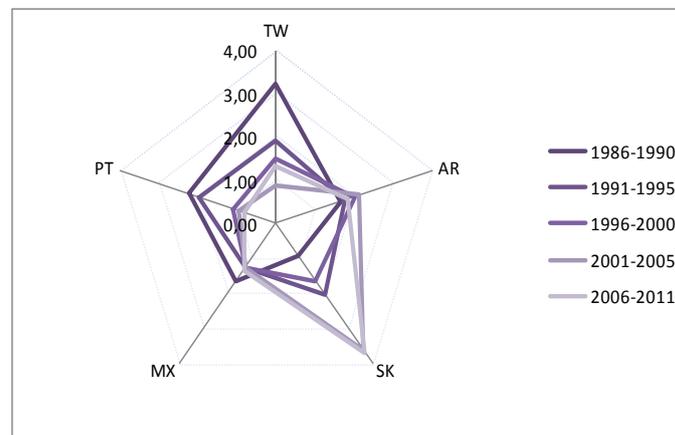
Group 3 contains medium or small size developed countries but with late processes of industrialization and with technological delays respecting to leaders. Due to size, it is expecting that some of those countries will be highly specialized (cases of Singapore and Hong-Kong) what explain their higher distance to leaders. Excepting the case of Israel and Italy, the patents share distributions in all the countries of that group trends to converge to leaders' from mid-eighties (Figure 3).

Figure 3. Technological distance with leaders (χ^2). Group 3* : Australia (AU), Spain (ES), Greece (GR), Hong-Kong (HK), Israel (IL), Italy (IT), New Zealand (NZ) and Singapore (SG)



(*): Countries between 20,000 and 30,000 \$ per capita in PPP by mean between 2000-2008.

Figure 4. Technological distance with leaders (χ^2). Group 4* : Taiwan (TW), Argentina (AR), South Korea (SK), Mexico (MX) and Portugal (PT).

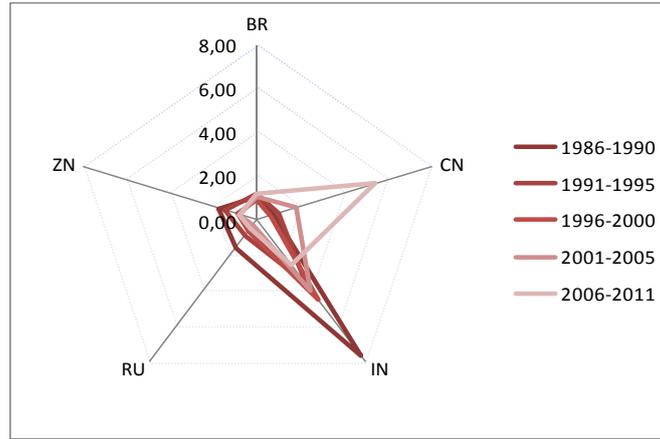


(*): Countries between 5,500 and 20,000 \$ per capita in PPP by mean between 2000-2008.

Group 4 includes catching up countries, also with technological and development delays respecting to leaders. That explains the highest initial distances when compared with other groups. As in the others, most of countries show a trend to convergence, even maintaining higher distances that other groups at the end of the analyzed periods. The exceptional case is given by South Korea which presents a growing tendency to diverge. As in the other cases, that observation is due the growing and strong specialization of South Korea in audio-visual and telecommunications technologies (Figure 4).

Finally, Group 5 presents interesting observations. In first place, that group includes all the BRICs countries and South Africa. This group is characterized by developing countries with recent fast growths, both in income and technological terms. As it was a characteristic in the other groups, most of countries in Group 5 present trend to converge. Brazil maintained its distances almost constant along periods and started a tendency to diverge only in the last period. India, Russia and South Africa followed a path to convergence uninterrupted, what permit to observe a strong reduction of distance in the Indian case. Only Russia inverted its trend in the last period increasing moderately the distances with leaders. However, China constantly increased its distances to leaders following a trend to diverge. And, as observed in the other cases, this trend is consequence of a strong specialization in audiovisual and telecommunication technologies, especially in the last period (Figure 5).

Figure 5. Technological distance with leaders (χ^2). Group 5* : Brazil (BR), China (CN), India (IN), Russia (RU) and South Africa (ZN).



(*): Countries below 5,500 \$ per capita in PPP by mean between 2000-2008.

As rhythms, paths and technological spillovers of technical change are dissimilar across technologies, a question emerges: is specialization in specific technical fields conducting to aggregate technological convergence or divergence? Or, in other way, is the technological specialization related to the evolution of technological gaps between countries? To test this possible linkage there will be defined three different measures of Ricardian technological specialization, this is, measures that considerate the importance to be specialized in some technologies over others. First one has a strong dynamic character and it is calculated as the Revealed Technological Advantage (RTA)⁴ for each initial period (1986-1990, 1991-1995, 1996-2000, 2001-2005 and 2005-2010) on technologies whose growth of patents share between the initial and the following period was positive (SRD), this is, according to the evolution of technological paradigms along eighties, nineties and two thousands (see annex 1). The second has a static character and it is calculated as RTA in each period on technologies whose growth of patents share between 1986-1990 and 2005-2010 periods was positive (SRM). That technologies were Information technologies, Audio-visual technologies and telecommunications, Medical technology, Biotechnology, Engines and pumps, Oil and basic material chemistry, Pharmaceuticals and cosmetics, Semiconductors Transport, Electronic devices, Electrical engineering and Consumer goods. Finally, the third indicator for specialization was RTA in Jungmittag's R&D Intensive sectors for a level of aggregation of 30 technical fields according to FISIR classification (see annex 2) for each of the same five periods above (SRJ).

To test the role of technological specialization on technological convergence we look for evidence of a negative correlation between per capita patents growth (p_{pc}^t) and the initial level of the per-capita patent stock (P_{pc}^0). First, it was estimated an unconditional regression of the patents per capita growth rates in the period 1986-2010 on the log of the patents per capita in the initial subperiod (1986-1990). The estimation confirms the existence of a negative correlation between both variables. This original equation to estimate the β -convergence was after expanded to include the specialization variables in two different ways:

1. $p_{pc}^t = \alpha + \beta \ln P_{pc}^0 + \xi s_i$, where s_i is the rate of growth of specialization variables (equations 1, 2 and 3 in table 3).
2. $p_{pc}^t = \alpha + \beta \ln P_{pc}^0 + \xi S_i^0$, where S_i^0 is the specialization value variables in the initial period (equations 4, 5 and 6 in table 3).

⁴ RTA is calculated as $\frac{p_{ij}}{p_{iw}}$, where p_{ij} is the j-country share of patents in i-technical field and p_{iw} is the share of patents in the same technical field for the area of reference.

The parameter that represents β -convergence remains around 0.13 and 0.15 independently the way the model is expanded, and the associated variable ($\ln P_{pc}^0$) also remains significant. On the contrary, none specialization variable is significant by observing p -values and t . Parameters relative to growth specialization reveals a positive association, this is, to be ‘well specialized’ would be positively associated with technological convergence. That association is observable for the three measures of good-specialization. Parameters relative to initial specialization show a negative relationship for dynamic and static definitions of ‘good specializations’ (SRD and SRJ), this is, the higher the initial level of specialization in good technologies is, the lower the technological convergence will be.

Table 3. Technological specialization and technological aggregate convergence*

	Growth of specialization variables			Initial values of specialization variables		
	(1)	(2)	(3)	(4)	(5)	(6)
c	.50754	.05145	.056258	.049495	.04715	.04908
t	1.46	1.55	1.68	1.50	1.48	1.49
P-value	0.153	0.131	0.102	0.145	0.150	0.146
$\ln P_{pc}^0$	-.01369	-.01315	-.01494	-.01346	-.01272	-.01320
t	-1.80	-1.87	-2.13	-1.85	-1.97	-1.92
P-value	0.082	0.070	0.041	0.073	0.057	0.064
SRD	.15316			-.00896		
t	0.22			-0.21		
P-value	0.829			0.836		
SRM		1.7774			.06521	
t		1.40			0.79	
P-value		0.171			0.433	
SRJ			2.2790			-.00708
t			1.19			-0.14
P-value			0.245			0.890

(*); measured as the rate of growth of patents per capita stocks. Source: Patents from Space Bulletin, EPO, 1978-2011. Population from World Penn, data for 34 countries.

To test the association between disaggregate convergence and initial technological specialization, it will be used a fixed effects regressing:

$$\chi_{it}^2 = \beta_0 + \beta_s S_{it} + \delta_t D_{t1} + \alpha_i + u_{it},$$

where χ_{it}^2 is the chi-square indicator, previously defined, by country and period; time effects have been added to control the particularities that affect data during that period, so, D_{t1} is a dummy variable for the first period; α_i takes the time invariant unobservable factors and u_{it} is the error term. S_{it} is the Ricardian technological specialization variables. Additionally, it was defined the Smithian specialization (D_j), which consider the degree of specialization no matter on what kind of technologies. Denoting s_{ij}^2 as the patent share of i -technology of j -country and M as the total number of technical fields, the Smithian specialization can be calculated as a diversification index:

$$D_j = \frac{(1 - \sum_{i=1}^m s_{ij}^2)}{1 - 1/M},$$

Table 4. Technological specialization and technological disaggregate convergence*

	(EQ1: SRD)	(EQ2: SRM)	(EQ3: SRJ)	(EQ4: SS)
β_0	0.0160 (5.86)	0.0060 (1.10)	- 0.0072 (-1.00)	0.2143 (5.86)
β_s	-0.0036 (-1.42)	0.0063 (1.39)	0.0215 (2.75)	-0.2084 (-5.55)
δ_t	0.0034 (2.50)	0.0038 (2.76)	0.0043 (3.18)	0.0021 (1.70)
<i>F-test (a)</i>	4.13	3.97	7.19	19.33
<i>Prob>F</i>	0.018	0.021	0.011	0.000

(*); measured as chi-square of national patent structures. Source: Patents from Space Bulletin, EPO, 1978-2011.

Results are reported in table 4. SRD has low significance and a negative sign indicating that to be specialized in dynamic technologies at the initial period drive to convergence to the leaders' technological structure, that is, to a reduction of χ^2 values. SRM and SRJ show positive signs. The static specialization (SRJ), when defined in terms of R&D intensity has a negative and significant association with disaggregate convergence, that is, higher specialization in R&D intensive technologies in previous period drives to higher distances with the leaders' technological structure in the next one. Finally, Smithian specialization shows a negative and significant relation between diversification and divergence. As expected, these results reveal that the higher diversified the technical structure in initial period was, the lower the distances with leaders will be in the next one by accelerated catching up. This is a good result that reinforces the importance of diversified technical bases to make easier and faster the catching-up process.

2. TECHNOLOGICAL SPECIALIZATION AND GROWTH

This section presents the model that allows to estimate the contribution of technological factors to the income growth as well as to observe productivity convergence. The derivation of that model is based on the approach initially developed by de la Fuente (2002) and later adopted and enlarged by Jungmittag (2004). It departs from the standard neoclassical framework but with a broader aggregate production function which will allow for convergence mechanisms others than diminishing returns such as technology diffusion, innovations and technological specialization. The augmented Cobb Douglas production function is:

$$Y_{it} = A_{it}K_{it}^{\beta_k}L_{it}^{\beta_l}P_{it}^{\beta_p}S_{it}^{\beta_s} \quad (1)$$

In this production function, for the country i in the period t ; Y_{it} denotes aggregate output, K_{it} is the private stock of physical capital and L_{it} is the employment. The level of technical efficiency is decomposed in three components: A_{it} represents the level of technical progress, initially exogenous, P_{it} (patent stocks) reflects the degree of efficiency due to the innovations and S_{it} captures the technological specialization of the country i . The main contribution of our model specification, related to that of Jungmittag (2004), relies on the definition of the technological specialization variables, as it will be discussed later.

Taking logarithms and first differences of the production function, the equation takes the form:

$$y_{it} = a_{it} + \beta_k k_{it} + \beta_l l_{it} + \beta_p p_{it} + \beta_s s_{it} \quad (2)$$

$$\Delta y_{it} = \Delta a_{it} + \beta_k \Delta k_{it} + \beta_l \Delta l_{it} + \beta_p \Delta p_{it} + \beta_s \Delta s_{it} \quad (3)$$

A key point of the de la Fuente and Junmittags' approaches is to consider that the index of technical progress a_{it} (measured in logs) has two components: w_{it} an index of transferable technical knowledge and α_i a fixed effect, a term that takes into account specific, nontransferable and time-invariant national characteristics which may have an impact on productivity.

$$a_{it} = w_{it} + \alpha_i \quad (4)$$

The index of transferable technical progress w_{it} is partially endogenized as a function of the patent stock, technological specialization and the technological gap between a country i and the sample average, this is:

$$w_{it} = w_t + d_{it} \quad (5)$$

Where w_t is the average level of transferable technical efficiency of the countries in the sample. It is assumed that w_t is an exogenous variable whose variation is approximated by an exogenous constant plus a trend:

$$\Delta w_t = g + ct \quad (6)$$

And $d_{it} = w_{it} - w_t$ is the technological distance between a country i and the average. The evolution of that distance is assumed to follow the equation:

$$\Delta d_{it} = \epsilon \tilde{p}_{it-1} + \xi \tilde{s}_{nt-1} - \mu d_{it-1} + u_{it} \quad (7)$$

Where \tilde{p}_{it-1} and \tilde{s}_{nt-1} are, respectively, the patent stock and the technological specialization of country i in the previous period measured in differences with the average of the group of countries and u_{it} is an identically independently distributed error term. Then, the technical progress differential of a country depends on its relative innovation and specialization level and on the technological gap that it maintains with the average group. The coefficient of the variable d_{it} should be negative if the assumption of an existing process of technological diffusion among countries is accepted.

A remarkable implication of this specification is that, *ceteris paribus*, the rate of technical progress should be higher in less developed countries. So, the sign of the coefficient μ will allow us to test the hypothesis that there is technological convergence across countries. If the coefficients ϵ, ξ are different from zero, such convergence would be only conditional, this is, each country converges in the long run to a stable level of relative technical efficiency that would be determined by the innovation and specialization level and the speed of technological diffusion (de la Fuente, 2002:581).

Considering (5) and (6), the rate of technical progress in country i during period t will be given by:

$$\Delta w_{it} = g + ct + \epsilon \tilde{p}_{it-1} + \xi \tilde{s}_{nt-1} - \mu d_{it-1} + u_{it} \quad (8)$$

Substituting this expression into (4) and (2) we obtain a specification of the production function in first differences in which the rate of technical progress in each country is expressed as a function of its relative innovation and specialization level and its transferable technological gap with respect to a fictional average country. Although d_{it} is not directly observable, the production function can be inverted and write d_{it} as a function of observable variables and coefficients to be estimated. It is required to substitute (4) in (2), solve for w_{it} and substitute into (3). Finally, after introducing a set of dummy variables to control for the countries fixed effects, a specification of the empirical model in terms of observable variables is obtained.

$$\begin{aligned} \Delta y_{it} = & g + \mu \tilde{\alpha}_v + ct + \beta_k \Delta k_{it} + \beta_l \Delta l_{it} + \beta_p \Delta p_{it} + \beta_s \Delta s_{it} + \epsilon \tilde{p}_{it-1} + \xi \tilde{s}_{it-1} \\ & - \mu \left(\tilde{y}_{it-1} - \beta_k \tilde{k}_{it-1} - \beta_l \tilde{l}_{it-1} - \beta_p \tilde{p}_{it-1} - \beta_s \tilde{s}_{it-1} - \sum_{i=1}^N \theta_i DC_i \right) + u_{it} \end{aligned} \quad (9)$$

Where the sub-index v denotes the reference country and the coefficient of the i -th country dummy DC_i has the form of $\theta_i = \tilde{\alpha}_i - \tilde{\alpha}_v$.

Empirical model and results.

The empirical analysis consists of the econometric estimation of the equation (9). As the model contains multiplicative terms in the coefficients, it needs to be estimated by Non-Linear Least Squares. The data sources are OECD Stats Database (Organization for Economic Co-operation and Development), AMECO Database, the annual macro-economic database of the European Commission's Directorate General for Economic and Financial Affairs (DG ECFIN) and European Patent Office, Space Bulletin, 1978-2011. To test the model it will be used a panel data for a sample of 23 countries between 1980 and 2010. The definition and the sources of the variables used in this section are:

1. y_{it} : *Real Gross Domestic Product at Purchasing Power Parity* (2005 prices). Expressed in logarithms. Data proceed from the OECD Stats Database.
2. k_{it} : *Real net capital stock*. Expressed in logarithms. The original variable Net Capital Stock for the total economy at 2005 constant prices in national currency has been converted into PPP US \$. The data source that allows using real net capital stock is the AMECO Database, which reduced the set of countries to 23⁵.
3. l_{it} : *Domestic Civilian employment*. Expressed in logarithms. It is equivalent to civilian labor force minus total unemployment, includes residents as well as non-residents working for resident producer units. Data are taken from the AMECO Database.
4. p_{it} : *Patents stock*, from European Patent Office (EPO), Space Bulletin, 1978-2011. The preference for EPO instead UPSTO (US patent office) is based on the no bias country criterion, which is especially important for international comparisons. Due to the patent data disponibility, it was only possible to work with five temporal sections per country. This variable takes the accumulated patents in each period from the initial period 1978-1985. It was not applied any depreciation function as in vintage capital models for two reasons. First one, of theoretical nature, because in this study, patents are used as a proxy of technological advance and, in neoschumpeterian tradition, this is a process of creative accumulation, and not a creative destruction process, which means that knowledge does not depreciates, but accumulates; ii) of empirical nature, because any rate of depreciation would be random and at the discretion of the author, given that, even assuming that knowledge depreciates, the rate of depreciation varies from technology to technology and it is impossible to estimate.
5. s_{it} : *Technological specialization variables*. Measures for technological specialization are the same as defined above, this is, three variables of Ricardian specialization (S_{RD} , S_{RM} and S_{RJ}) and one for Smithian specialization (S_S).

In the estimation of the equation (9), it will be assumed that the sum of the elasticities of the physical capital and the labour equals unity. That assumption of constant returns to scale in labour and physical capital was introduced by de la Fuente (2002) and Jungmittag (2004) during the process of endogenization of a part of the technical progress⁶. In that process, it is also assumed that production

⁵ The countries are: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom and United States.

⁶ The estimation of the model without imposing any restriction on the value of the parameters was previously made obtaining results very similar to those obtained with the specification included in Table 4. So, this restriction hardly has any impact on the value of the model's parameters.

factors elasticities (L, K, P and S) are equal for all the countries of the sample, although the growth rate of the technical progress can vary between the countries⁷.

Table 4 shows the estimations' results for the four equations, one for each of the specialization variables defined. Comparing the four columns of the table, we observe that the coefficients of the labour factor are around the usual magnitudes. The coefficients of the physical capital stock are shown into brackets, underline that due to the restriction on the production function parameters ($\beta_k=1-\beta_l$), their value has been imposed rather than estimated. The elasticities of the patents stock variable are similar in the four estimations. Its impact on economic growth is positive and significant but practically negligible compared to those obtained in other studies (e.g. it is around 0.037 in Junmittag, 2004). By contrast, its relative level (\tilde{p}_{it-1}) shows very similar coefficient values except for the second regression and with negative signal. In the sample, countries with higher technological distances to mean had lower rates of per capital GDP growth, which indicate some evidence of no convergence.

The variable that captures the relative distance in specialization (\tilde{s}_{it-1}) shows mixed results. The estimated coefficients of statics measures (SRJ and SRM) are positive and significantly different from zero at the usual levels of significance, which agree with Jungmittag's results. This is increasing good specializations (in R&D intensive sectors or in dynamic technologies between eighties and two thousands) corresponds to higher levels of income growth. Nevertheless, good specializations in dynamic technologies by period seem to have a positive and moderate effect on income growth at a significance level below 10%. Relative positions of Smithian specialization are not significant, which is expected given the homogeneity that characterizes the diversification of technical bases in that sample of countries.

Table 4. Empirical results of model.

	(EQ1: SRD)	(EQ2: SRM)	(EQ3: SRJ)	(EQ4: SS)
$g + \mu \tilde{\alpha}_v$	0.1008 (3.40)	0.1171 (4.38)	0.1235 (4.50)	0.115746 (3.36)
c	0.0102 (2.98)	0.0129 (5.26)	0.0103 (3.98)	0.0098 (3.32)
β_l	0.7461 (12.25)	0.7021 (13.40)	0.7053 (12.94)	0.7283 (13.03)
β_k	[0.2539]	[0.2979]	[0.2947]	[0.2717]
β_p	5.05e-07 (2.73)	4.20e-07 (2.76)	4.58e-07 (2.93)	3.84e-07 (2.12)
β_s	-0.0129 (-2.00)	0.0501 (5.20)	0.0815 (4.27)	0.2334 (1.52)
ϵ	-0.00512 (-4.42)	-0.0101 (-3.86)	-0.0036 (-3.59)	-0.00473 (-3.98)
ξ	0.0088 (1.31)	0.0340 (3.06)	0.075 (3.81)	0.0352 (1.29)
μ	-0.1149 (1.31)	-0.1166 (1.11)	-0.154 (1.61)	-0.1286 (1.12)
<i>Adj. R 2</i>	0.9094	0.9272	0.9401	0.9232
<i>F-test (a)</i>	31.51	44.50	42.08	30.43
<i>SSE (Sum of squares error)</i>	0.007224	0.005221	0.00556	0.007459

(a) At the 0.05 significance level

⁷ The introduction of n-1 country dummies variables in the estimations allows each country to have its own intercept but to share the same slopes of regressors.

With regard to the variables that capture the change in technological specialization (S), the results are different according to the definition of 'goodness' for specialization. The coefficients are significant for a significance level of 1% in estimations with static measures of good technological specialization (SRM and SRJ), which matches to the Jungmittag's results. In both cases, the coefficient shows a positive sign. The sample is composed by developed countries, which specialized in the R&D intensive sector indicated by Jungmittag and that built advantages from the information and telecommunications and electronic paradigms along nineties. So, this kind of specialization is clearly relevant in their income growth. Alternatively, dynamic measure of 'good specialization' presents an estimated parameter also significant, but with negative sign. From the beginning of two thousands, the huge opportunities derived from the technological paradigm of the information and telecommunications and electronics seems to be exhausted in their own and other technologies took importance (see annex 2). As countries in the sample have no specialization in this kind of technologies from two thousands, the sign became negative.

Finally, the coefficient that captures the rate of technology diffusion is significant at a significance level of 10% in the third estimation (in the others is lower). The estimations indicate a rate of diffusion around 15% which is quite higher than the value obtained by others studies (Jungmittag, 2004). The negative sign of this variable indicates that technological diffusion is a result of the catching-up process. This means that technological diffusion is higher as lower the initial technological position of a country is, that is, as higher its gap to the technological frontier is.

The sample of countries is quite homogenous, that is, there are not significant technological gaps across the considered countries. Proximity affects mainly to European Union countries in the sample. But most of the countries are opened economies in terms of international trade and mobility of factors. In this sense, the degree of international integration can be the main channel of technological diffusion across them.

CONCLUSIONS

This paper aimed to contribute to the theory of convergence by emphasizing the role of technological specialization. In this sense, economic literature recognizes that 'good specializations' should induce to increase productivity growth because of the positive spillovers that emerge from them and because 'good specializations' are related to sectors with high income elasticity with higher potential of growth. Empirical works use different measures for 'good specialization'. Under a *static* point of view, the good technologies relative to good sectors are defined by the intensity in R&D. Under a dynamic point of view, the technological opportunities are changing in two senses: i) as a result of the emergence of new technological paradigms; and ii) due to the set of possibilities that recent paradigms offer through the spread across all sectors, allowing the development of related technologies.

So, the objective of this work was to test the role of *good* technological specialization in the evolution of aggregate and disaggregate technological convergence for 35 countries and for the observed growth of 22 countries, both between 1980 and 2010.

For the first analysis it was observed the evolution of technological convergence for 34 countries. This set included developed and developing countries with significant technological gaps between them. Absolute measures (the standard deviations of patents per capita) showed that the technological divergence between countries become higher along time. On the contrary, relative measure (σ -convergence) showed a trend to converge along the whole period. β -convergence, measured as patents per capita rate of growth, confirmed this result and estimate a rate of convergence around 13%. Disaggregate convergence was measured by chi-squared statistic respecting to the leaders (Japan, United States and Germany). The general tendency is that countries converge with leaders with some exceptional cases. The most representative ones are Island, Norway, Finland, Canada, Italy, Israel, South Korea and China.

Divergence cases relative to Finland, South Korea and China are a result of the path to a strong specialization in audiovisual and telecommunication technologies in the last two decades.

To test the role of technological specialization in the observed convergence, it was extended the β -convergence regression by the inclusion of three measures of 'good specializations'. First measure considers as 'good specialization' the national initial position in technologies that were dynamic in the next period (SRD). Second one consider the national specialization in technologies that were dynamic between the initial (1985-90) and final period (2005-2010) (SRM). Third one considers, statically, that good specialization is associated with technologies relative to intensive in R&D sector (SRJ). Results show that initial positions of technological specialization are negatively associated with convergence, but this association has low significance. There is also the observation about a positive relation between disaggregate divergence and increasing specialization in R&D intensive technologies and the negative and significant association between diversification and divergence, that is, with lower distances between leaders and followers.

The contribution of technological specialization to growth was tested using an extended model of endogenous growth that includes additional convergence mechanisms than diminishing returns, such as technology diffusion, technology and technological specialization. The model shows that specialization matters to growth. But some qualifications must be done. Firstly, static measures of good technologies are positively associated with income growth, but not dynamic measures. Due to the evolutionary nature of technical change, what is 'good specialization' today will not tomorrow and what are advantages at the present cannot be in the future. This is especially relevant if still is considered that countries delay to change their specialization patters. Secondly, the sample considers just developed countries due to the model demands capital stocks variable and AMECO database just offer information for that restricted number of countries. The question is that none conclusion about the role of technological specialization can be obtain for developing and catching-up countries, even when its effect can have been quite important in Asian countries and BRICs. This is undoubtedly a challenge for future works.

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Annex 1: Good technologies under a dynamic and evolutionary view of paradigms: technologies with positive growth of patent share.

RANK	1986-1990, 1991-1995		1991-1995, 1996-2000		1996-2000, 2001-2005		2001-2005, 2006-2010	
1	Biotechnology	34,61	Information technology	62,61	Medical technology	9,48	Oil and basic material chemistry	30,43
2	Audio-visual technologies, telecommunications	29,45	Audio-visual technologies, telecommunications	41,11	Oil and basic material chemistry	8,85	Medical technology	18,63
3	Information technology	27,98	Pharmaceuticals and cosmetics	33,91	Consumer goods	4,30	Consumer goods	12,19
4	Organic chemistry	14,09	Engines, pumps	33,38	Pharmaceuticals and cosmetics	4,20	Chemical engineering	11,64
5	Medical technology	12,26	Biotechnology	26,19	Transport	2,57	Civil engineering	9,70
6	Optics	11,60	Medical technology	19,54	Audio-visual technologies, telecommunications	2,09	Semiconductors	8,90
7	Electronic devices, electrical engineering	6,49	Transport	16,74	Control and measurement technology	1,81	Electronic devices, electrical engineering	7,47
8	Semiconductors	5,27	Control and measurement technology	2,38	Engines, pumps	1,60	Engines, pumps	7,32
9	Oil and basic material chemistry	3,06	Semiconductors	0,47	Food and agriculture	1,24	Food and agriculture	5,04
10					Materials processing	0,59	Environmental technologies	2,72
11					Mechanical elements	0,41	Surfaces	2,62
12							Nuclear engineering	2,57
13							Space technology	2,48
14							Control and measurement technology	1,62
15							Transport	1,07

Source: Own elaboration from EPO, Space Bulletin, 1978-2011.

Annex 2. Good technologies under a static criterion: R&D intensive industries and concordance to FISIR classification

	FISIR CLASSIFICATION		JUNGMITTAG CLASSIFICATION
1	Electronic devices, electrical engineering	HLT	Electrical machinery (ex. Radio TV, communications)
2	Audio-visual technologies, telecommunications	LE	Radio, TV & communications
4	Information technology	LE	Office and computers machinery
6	Optics	HLT	Professional goods
7	Control and measurement technology	HLT	Professional goods
8	Medical technology	HLT	Professional goods
9	Organic chemistry	HLT	Chemical (no drugs)
10	Macromolecular chemistry, polymers	HLT	Chemical (no drugs)
11	Pharmaceuticals and cosmetics	LE	Drugs & medicines
15	Chemical engineering	HLT	Chemical (no drugs)
19	Oil and basic material chemistry	HLT	Chemical (no drugs)
21	Machines, tools	HLT	Non electrical machinery (ex. office & computing)
22	Engines, pumps	HLT	Non electrical machinery (ex. office & computing)
26	Transport	HLT	Motor vehicles / Other transport equipment
28	Space technology	LE	Aircraft, guided missiles & space vehicles

Following Jungmittag (2004), HLT are High level technologies and LE leading edge technologies.