FOLHA DE ROSTO

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Titulo: "**On the evolution of technological specialization patterns in developing countries: comparing Asia and Latin America**".

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Resumo. Este trabalho explora o papel da oportunidade tecnológica e a cumulatividade na evolução dos padrões de especialização tecnológica (PET) dos países em desenvolvimento. A análise empírica utiliza dados de patentes entre 1980 e 2010 para 9 países latino-americanos e asiáticos. O trabalho mostra que os novos paradigmas tecno-económicos dos anos oitenta e a internacionalização mundial dos noventa aceleraram o processo de catching up de ambos os grupos de países, mas com algumas diferenças entre América Latina e Ásia. Todos os países aumentaram sua parcela tecnológica no mundo, diversificaram suas bases tecnológicas e reduziram seus níveis de especialização. Todavia, os países asiáticos atingiram um melhor desempenho e criaram competência e capacitações em tecnologias relacionadas com os novos paradigmas tecno-económicos. Não há evidencia de que o aproveitamento de janelas de oportunidade dependa de corretas ou incorretas especializações iniciais. PET podem reverter com incentivos apropriados e suscetíveis de mudanças ao longo de processos de catching up.

Abstract. This paper explores the role of technological opportunity and cumulativeness in the evolution of technological specialization patterns (TSP) in developing countries. Empirical analyses uses patent data between 1980 and 2010 of 9 Asian and Latin American countries. The paper shows that the new techno-economic paradigms of the eighties and the world internationalization from the nineties accelerated the catching up process in both groups of countries, but with some differences between Latin American and Asian. All countries increased their technology share, diversified their technological bases and reduced their levels of specialization. However, the Asian countries achieved a higher performance and created competences and capabilities in the technologies related to the new techno-economic paradigms. There is no evidence that taking the advantages from open windows of opportunity depends on correct or incorrect initial specializations. TSP are reversible with the appropriate incentives and are suitable to change along any catching up process.

Keywords; Technological opportunity, cumulativeness, technological specialization patterns, Asia, Latin America, catching-up, technological irreversibility, persistence, mobility.

Palavras chave: Oportunidade tecnológica, cumulatividade, padrões de especialização tecnológica, Ásia, América Latina, catching-up, irreversibilidade tecnológica, persistência, mobilidade.

JEL Classification; O30, O52, O54

Área 9. Economia Industrial e da Tecnologia

On the evolution of technological specialization patterns in developing countries: comparing Asia and Latin America.

1. Introduction.

The liberalization processes from the nineties resulted in deep changes in the world economy. One of them concerns to the national technological specialization patterns (TSP). Recent studies pointed out the evolution of national TSP responds to three factors (Urraca-Ruiz 2013a): the evolution of technological regimes, the induced allocation of technological resources by policies and institutional incentives and the structural change. This paper calls the attention to the first one. From technological regimes, the main factors affecting TSP are the technological cumulativeness and technological opportunity. Theory deals with technological cumulativeness as path dependent and therefore, a cause of stability or persistence of TSP. In this sense, empirical analyses on TSP should verify: (1) a difficulty to create specialization in technical fields where there are no previous absorptive capacity, especially if there are barriers to diffusion; (2) an easiness to increase previous specializations; and (3) low mobility levels. Empirical evidence in the eighties revealed that industrialized countries perform diversified TSP, while small and developing countries became more specialized in their technological profiles (Archibugi and Pianta 1992, 1994). Nevertheless, more recent empirical evidence showed that persistency is a phenomenon more associated to leading countries while mobility across technical fields trends to be higher and asymmetric in developing countries (Stolpe 1995; Laursen 2000; Mancusi 2001; Urraca-Ruiz, 2013a). Evidence showed that it was difficult to increase specialization in technical fields with no previous specialization but quite easy to move towards technical fields related to previous specializations. Furthermore, there was no evidence of persistence at high levels of specialization. On the contrary, high levels of specialization reverted to lower ones, being quicker and more drastic in smaller countries (Mancusi 2001; Roper and Hewitt-Dundas, 2008).

Literature identify two determinants for mobility: the technological opportunity (TO) and structural change. Technological opportunity represent new open "windows of opportunity" from achieved technological capacities given the new possibilities that technological paradigms offer. Open markets and competition incentive to take advantages from the new technological possibilities, which stimulate the internal innovation efforts. The reallocation of productive and technological resources in these terms are related to structural change and the industrial transformation. However, earlier empirical works on TSP evolution disregard the effect of economic integration and technological opportunity on innovative resources allocation, even when empirical analysis were performed on countries in processes of transition towards more integrated economic spaces.

Evolution of TSP acquire some specificities in developing countries. In first place, empirical evidence revealed that while industrialized countries distributed their innovative activities among a wider set of technologies, developing countries used to specialize in low-opportunity technologies (far from the technological frontier). This kind of specialization would have a perverse effect and constraint the long-term technological development (Archibugi and Pianta, 1994; Mancusi 2001; Montobbio and Rampa 2005). In second place, to find technologies in developing countries is a costly and hard process [even that asymmetric across technologies] at least for two reasons (Lall, 2000). First, because it is necessary to develop new capabilities -skills and tacit knowledge- to use and apply efficiently imported technologies; and second, because of the costs of coordination to create internal capabilities are high and asymmetric. As technological specialization reveals capabilities, TSP evolution depends more on the national ability to create new capabilities on new competences than to reproduce the old ones. Therefore, there are good reasons to think that in mobility and turbulence will be a major characteristic of countries along a process of building of competences.

This paper looks for empirical evidence about the determinants of the TSP evolution for developing countries -Asian and Latin American-. More concretely, the paper focus on the role played by technological opportunity for turbulence and cumulativeness for stability of TSP patters. There are two motivations in the comparison between Asia and Latin America. Both groups went through economic integration processes with the world, which represented important structural changes int their economies (Shafaeddin, 2005). Nonetheless, they followed very different productive and commercial patterns of specialization. As Asian followed a specialization pattern oriented to the production and exports of labor-intensive and knowledge-intensive products, Latin American followed a specialization pattern based on its principal national endowments: natural resources (Alcorta and Peres, 1998; Urraca-Ruiz, 2013b). The Asian success by catching up contrasts with the Latin America 'failure' characterized by its inability to develop strategic and pervasive technologies from its own competitive advantages.

The main motivation of this work is to contribute with empirical evidence about the specificities of the TSP evolution in developing countries in the following aspects. Firstly, by answering if it really exists some initial favorable TSP that allows future technological development better than any other does. Secondly by discussing if the Latin American specialization pattern did constrain its catching up process in two senses. First, because it did not allow taking advantages of technological opportunities associated to its specific pattern of specialization. Second, because the Latin American TSP restricted the change a more diversified one, confirming a certain irreversibility of technical change.

2. Theoretical framework.

Technology is the result of continuous knowledge production processes. From an evolutionary point of view, knowledge production processes involve, at the firm level, different kinds of learning activities to create and accumulate new knowledge (capabilities) in technological competences. At country level, national technological structures are the aggregation of technological competences [distributed by technical field] embodied in individuals, firms and institutions. Going along with productive structure, a technological structure is the distribution of technological capabilities built from specific allocations of technological resources across fields of technological knowledge (Meliciani 2002; Brusoni and Geuna 2003). A pattern of technological specialization (TSP) expresses the technological structure of a country in relative terms, this is, in comparison to another country or a group-of-countries of reference.

The literature points out that three are the determinants of TSP evolution: the properties of technological regimes associated to the initial specializations, the institutional incentives to the allocation of technological resources and structural change (Urraca-Ruiz, 2013a). From technological regimes, cumulativeness has an ambiguous effect on the TSP evolution. By one hand, cumulativeness represents the ‘continuity’ of technical change. Given that each technology has specific bases of knowledge, the rate and direction of technical change will depend on how countries learn [acquire and accumulate new knowledge from previous efforts] and develop absorptive capacity (Cohen and

Levinthal 1990; Malerba 1992; Malerba et al. 1997; Malerba and Montobbio 2000). At the firm level, the technological accumulation of competencies combined to market forces drives to persistence of innovative activities, and as a consequence, persistence of the leading technologies and persistence of the leading firms. As successful innovation generates quasi-rents that funds future R&D, innovating in period *t* increases the probability to innovate also in *t+1* (Malerba et al, 1997). The evolution of national TSP would represent the aggregated effect of persistence at the firm level, but also would include the path dependent character of the social process of learning concerning all organizations (universities, public research centers, government agencies, etc.). The result of persistence is the stability of TSP over time (Brusoni and Geuna 2003) in two senses. One, as the countries' ability to remain specialized in the same technical fields. And two, as the inability to move on from despecialization to the creation of growing technological capabilities in new technological competences. In this sense, cumulativeness introduces some level of irreversibility on the TSP evolution.

However, by the other hand, cumulativeness can also be associated to mobility, especially in developing countries, because it is closely related to the catching-up processes. The cumulative character of knowledge by learning processes to assimilation, adaptation and capacitation makes TSP evolution not just the result of a "unique historical process", but the result of combining specific relative factor endowments with the accumulation of national absorptive capacities (Stolpe 1995). Consequently, the evolution of TSP express the path of cumulativeness from leading advantages through absorption capacity and catching-up. If TSP follows a path from previous specializations, the result will be stability. Nonetheless, if countries are able to create new capabilities from the old ones, the result will be mobility and turbulence. Both phenomena are not excluding and can occur simultaneously, especially along economic integration processes when incentives to the allocation of resources changes and some structural change is expected.

Empirical evidence about the role of cumulativeness on stability confirms the theoretical previsions only partially. On one hand, greater levels of persistence are more common in large and industrialized countries, where leading technologies and firms trend to remain, but not necessarily in developing countries where new players can enter into the scene. In addition, mobility observed in developing countries are mostly associated to their process to build new technological capabilities, which no necessarily come from cumulated ones. On the other hand, persistence uses to be a phenomenon more related to despecialization than to specialization, being despecialization stability the main component of TSP stability (Mancusi 2001, 2003; Urraca-Ruiz, 2013a). In fact, mobility is usually high and asymmetric across technical fields, which means that it is more difficult to increase specialization in technological fields where there is a previous disadvantage but it seems to be easier to move from one specializations to another, transforming strong initial specializations into growing levels of diversification (Mancusi 2001). Fourth,

In relation to the role of technological opportunity on TSP there are two alternative hypotheses. On one hand, the direction of TSP mobility depends on initial 'correct' or 'wrong' specialization. Innovation process is cumulative and knowledge becomes more complex in the frontier. In order to achieve technological leadership, countries should previously develop technological competences on basic scientific and generic knowledge. Specialization in these type of competences yield advantages for technological progress due to their synergies with other technologies and the wider range for application in other activities [pervasiveness], and because they shorten learning and innovation processes [dynamism] (Huang and Miozzo 2004; Meliciani 2002; Montobbio and Rampa 2005).

Specialization in ‘inferior’ technical fields (lower opportunity) represent a constraint for developing countries unless they introduce proper institutional frameworks and public policies to diversify the technical base creating absorptive capacity to make possible the catching-up (Vertova, 2001; Jungmittag, 2004). In this sense, ‘incorrect’ specialization can be associated with technological structures at initial stages of technological development.

On the other hand, leading technologies and technological frontier are changing along with the evolution of technological paradigms. As technological paradigms evolve, initial leading technologies can mature while new ones emerge by taking the advantages and opportunities that new paradigms offer. This was the case of biotechnologies on agriculture and food or new materials on surfaces and semiconductors. Thus, what was “incorrect” specialization in one period may cease to be in the next one. The changing nature of technological opportunity across technologies explains why despite initial unfavorable specialization, some countries register high technological dynamism as long as some efforts are carried out (Laursen 1999; Meliciani 2002). In addition, the techno-economic paradigms affect the whole range of technological systems and new micro-paradigms emerge and develop. In the initial stages, when general knowledge is more relevant than specific knowledge, technological gaps as barriers to entry are low, temporary “windows of opportunity” are open, and developing countries that possess the relevant knowledge and techniques can catch up, even surpassing previous leaders (Perez and Soete, 1988:477). In this scenario, catching up is not only a question of relative speed, but also involves running in a new direction as an early entrant in a new technology system. Therefore, developing countries can experience mobility of this nature and TSP will be changing and unstable; and technology leaps can be observed. Afterwards, continuous innovation efforts, accumulation of knowledge and leadership in the markets will stabilize the new TSP until a new techno-economic paradigm emerges.

3. Patent Database.

The empirical analysis works on patent applications in the European Patent Office by six Asian countries (China, India, Singapore, South Korea, Taiwan and Hong-Kong) and three Latin-American countries (Argentina, Brazil and Mexico) between 1980 and 2010. EPO database represents the best source of information to international comparisons for several reasons. Firstly, because a simple patent is extensible to all Munich Convention member countries, which eliminates country bias of the domestic effect [like, UPSTO does]. Secondly, fee applications are relatively higher, which excludes from the database patents of low industrial value. Thirdly, EPO publishes grants and deposits of patents eighteen months after the application (by mean), while other bases are more delayed [for example, UPSTO only publishes after two years (by mean)] (Grupp and Schomach, 1999; Le Bas and Sierra, 2002; van Zeebroeck et al., 2006).

Patents are largely used to analyze technological competences at national and firm level because they represent results of formal or informal innovation efforts and provide detailed data in a regular and long time series grouped by firm, country, geographic location or technical field (Patel and Pavitt 1991). Nonetheless, there are also some limitations of patent data as a source of information to express national TSP. First, patents reveal distributions of competences in terms of disembodied technologies and codified knowledge across technical fields but they are insufficient to measure the distribution of capabilities. Technological capabilities should include also indicators on Embodied and Disembodied knowledge, Codified and Tacit knowledge and Generation and Diffusion of knowledge (Archibugi and Coco, 2005). Therefore, even considering the assumption that complementarities do exist between all three categories, the use of patents alone underestimates the set of aspects that transform a competence into a capability. Second, patents underestimate the contribution or closeness of scientific bases to the creation of the technical bases because of "the lack of engineering capabilities to embody scientific results in profitable products" (Brusoni and Geuna, 2003). In this sense, a country could have strong competences and capabilities in development weakly supported by basic knowledge (ibidem). Third, measuring technological specialization to the development of specific products and industries involve a classification of technological fields that does not respond to the usual ones in patent classifications. Therefore, additional criteria for product aggregation are necessary. Fourth, some national technological competences can be underestimated when they are built on non-patentable technologies (or bases of knowledge) or on technologies that are not protected by patents.

Finally, four major methodological aspects worth to be noted in relation to the treatment given to the information contained in the patent database. First, patents are de only one source of information that synthetize national R&D efforts with potential of innovation by technical field. Second, the inventor residence gives the nationality to the patent. Third, as national competences must include all the agents and organizations that create competences, database includes patents filed by any applicant, as be firms, universities, public research centers, government agencies and independent inventors (Brusoni and Geuna 2003). Fourth, one patent represent a technology that combine different types of knowledge. For this reason, one only patent may be classified in more than one technical field. This paper uses all technical fields from each patent to account technological competences. This means that a single patent becomes as many competences as technical fields it contains.

4. The evolution of technology specialization patterns.

4.1. Mobility and instability.

The traditional measure of technological opportunity is the growth of the patents share by technology ($\dot{p}_i$). Nevertheless, as the patent database was extended to account technological competences, the indicator shape the growth of the share of the competences involved in the production of a i-technology on the total world competences ($\dot{c}_i; c_i > p_i$). This indicator depends on the dynamism of the main technologies to which the competence (technical field) is linked in, but also on the frequency that the competence complements other technologies, this is, their pervasiveness.

The most dynamic and pervasive technologies between eighties and the two thousand are shown in Table 1. The temporal choice obey to two factors that altered the distribution of technological opportunities across technologies along the nineties. The nineties represent the decade of the expansion of the new technological paradigms (electronics, telecommunications, biotechnologies, semiconductors and new materials), which represented open windows of opportunity for developing countries. In addition, most of countries in the sample liberalized their international markets [commerce of goods and services, capital openness, or both], which accelerate the technology transfer and the catching up. Data reveals that the main paradigms emerging in the eighties (telecommunications, information technologies, audiovisual, semiconductors or electronics) are among the most dynamic and pervasive technologies. They are also considered as technologies of high impact on exports and growth (Lall, 2000). Nevertheless, others like biotechnology, optics or pharmaceuticals and cosmetics presented a low opportunity or pervasiveness in the same period. Alternatively, some competences linked to medium-low technological intensity products in exports showed high opportunity and pervasiveness along time like Surfaces, Handling, Consumer Goods or

Material processing. Technological competences related to products based in natural resources presented a low opportunity and pervasiveness.

The analysis by country shows that, excepting Hong Kong, all Asian countries increased their share of competences in dynamic technologies, being especially strong in South Korea (semiconductors and telecommunications); China (telecommunications) and India (telecommunications and audiovisual technologies). The expansion of competences was not only restricted to dynamic and pervasive technologies, but also to stagnant. This configures a path of evolution based on diversification of the technological base by complementarity. Singapore and Taiwan show moderate increments of their shares, with the exception of Singapore in Semiconductors. Hong-Kong address losses of share in most of dynamic technologies that are not offset with increases of shares in stagnant technologies.

Table 1. Rate of Growth of patent-share (competences) ranked according to the dynamism of technological opportunity and pervasiveness ($\dot{c}_{ij}$).

Technical fields ranked by Technological Opportunity Dynamism	Brasil	Argentina	Mexico	Hong Kong	Singapure	Taiwan	South Korea	China	India	Tech for Exports (1)
Dynamic technological opportunity or high pervasiveness between (1980-90) and (2000-2010)										
Telecomunications	0,15	2,08	0,54	-0,55	34,35	15,31	97,04	290,02	170,19	High
Information technology	1,12	2,04	8,73	-0,36	7,12	12,41	42,88	60,76	61,12	High
Medical technology	0,42	0,55	2,56	-0,14	38,40	2,74	11,19	8,10	4,50	High
Nuclear engineering	1,01	1,12	3,42	-0,39	3,42	2,68	8,97	9,22	7,06	-
Surfaces	17,10	1,05	0,83	0,33	14,15	15,83	11,44	21,60	5,18	Low
Handling	1,24	0,24	0,98	-0,39	12,97	2,63	12,24	5,72	26,38	Low
Semiconductors	-0,42	1,92	-0,86	3,80	61,98	25,61	114,90	26,60	4,25	High
Audiovisual tecnologies	-0,07	-0,50	2,27	-0,36	21,76	13,64	38,31	35,45	78,36	High
Consumer goods	1,64	2,46	2,66	0,71	5,40	2,33	31,04	17,16	14,13	Low
Chemical engineering	3,12	3,35	-0,24	1,00	20,11	7,29	15,49	17,43	2,07	
Electronic devices, electrical engineering	3,60	0,45	8,19	-0,27	3,64	7,48	39,79	30,99	7,35	-
Control and measurement technology	1,43	1,20	5,41	-0,26	11,62	5,20	10,13	16,94	12,25	High
Materials processing	8,89	28,37	4,55	-0,15	14,46	4,39	19,73	10,37	12,96	Medium
Stagnant technological opportunity or low pervasiveness between (1980-90) and (2000-2010)										
Machines, tools	1,28	0,16	5,96	5,38	17,56	1,61	119,04	34,75	44,23	Medium
Food processing	1,58	0,24	3,94	7,24	19,32	8,34	119,69	29,60	5,59	Resource
Civil engineering	1,16	3,79	0,74	-0,02	1,67	1,60	18,58	35,84	35,87	-
Transport	2,58	11,42	2,54	1,02	3,62	4,58	38,64	5,04	12,87	Medium
Oil and basic material chemistry	5,36	4,57	2,13	0,63	7,10	5,83	32,95	39,87	55,92	Resource
Materials, metallurgy	4,59	8,18	2,06	4,51	6,87	9,40	67,77	9,11	6,07	Low
Engines, pumps	4,64	0,35	1,21	0,07	1,70	5,00	28,44	17,81	21,49	Medium
Optics	0,67	-0,15	1,45	-0,24	12,71	17,61	63,69	18,35	6,52	High
Mechanical elements	3,54	0,68	4,43	3,61	14,36	1,75	130,59	28,42	10,34	Medium
Thermal processes	2,17	3,02	10,23	1,15	13,34	4,32	102,98	15,29	6,20	Medium
Space technology	6,52	0,25	-0,16	3,18	0,83	12,54	32,44	2,57	0,32	High
Food and agriculture	0,97	0,24	2,93	0,59	24,25	5,15	51,57	15,31	5,51	Resource
Pharmaceuticals and cosmetics	2,00	1,72	7,37	0,77	11,38	6,53	31,11	50,94	10,35	High
Environmental technologies	6,43	0,48	3,14	3,42	10,37	8,40	40,26	30,52	10,22	Medium
Biotechnology	6,16	1,30	5,05	3,91	6,84	13,88	27,43	30,36	10,16	High
Macromolecular chemistry, polimers	3,11	1,99	0,11	4,43	13,03	10,28	24,64	28,24	12,86	Resource
Organic chemistry	-0,06	2,13	-0,06	-0,06	0,04	18,80	84,45	6,03	24,01	Medium

(1) According to Lall (2000). Empty spaces relates to technologies not directly linked to a single product or industry in trade.

Source: EPO, Space Bulletin 1978-2010 and own elaboration.

Latin American countries, with traditional TSP based on the exploration or natural resources, also increased their contribution to the world technological competences in dynamic technologies, but in much less extend, losing share in Audiovisual and Semiconductors. The highest growth were obtained by Brazil in Surfaces; by Argentina in Materials processing; and by Mexico in Information Technologies and Electronic Devices. The trend is quite similar in competences related to technologies of stagnant opportunity or low pervasiveness, which means a TSP evolution partially based on the substitution of the technological efforts from one competences to another.

To test the hypotheses about mobility and instability two exercises will be done. The first one tests if there are initial distributions that favors the growth of technology share in the following periods better than others do. Shift-share analysis testes this by decomposing the rate of growth of a share of total technological competences of a country with respect to an area of reference ($\dot{c_J}$) in three different effects (Laursen 1999):

$$\dot{c_J} = \sum_{\iota} s_{\iota J}^{t-1} \dot{c_{\iota J}} + \sum_{i} s_{ij}^{t-1} \dot{o_{\iota J}} + \sum_{i} s_{ij}^{t-1} \dot{c_{\iota J}} \dot{o_{\iota}}$$

Where ($\dot{c_{\iota J}}$) denotes the growth of the j-country share in the i-technology over the same technology in the world (presented in table 1); ($\dot{o_{\iota}}$), the growth of the i-technology share, which is the proxy of its technological opportunity; and (s_{ij}^{t-1}) the share distribution of the j-country by i-technology in the initial period. The first component, $\sum_i s_{ij}^{t-1} \dot{c_{\iota J}}$, named 'technology share effect', measures the fraction of growth due to the dynamism of national patenting activity strictly (technological activity in the wide sense). The second factor, $\sum_i s_{ij}^{t-1}\, \dot{o_{\iota}}$, named 'structural technology effect', measures the fraction of growth due to a given initial specialization pattern. This component measure the effect of initial 'correct' or 'incorrect' specializations. A positive signal of this component means that the country had an initial distribution of its competences more concentrated in the technologies that registered the higher rates of growth, and negative if the contrary. Therefore, the higher specialization in dynamic technical fields is ($\dot{o_{\iota J}} > 0$), the stronger effect of technological opportunity will be. The third factor $\sum_i s_{ij}^{t-1} \dot{c_{\iota J}} \dot{o_{\iota J}}$ shapes a residual effect called 'technology adaptation effect'. It takes negative values when the country left high TO fields (or went into staged TO fields); and takes positive values when the country went into high TO fields (or went out staged TO fields). That factor represents a measure of the mobility conducted by technological opportunity and patenting activity (in the strict sense).

Shift-share results in table 2 shows that Latin American countries registered high growths of their share of patents [competences] in the world (Total effect): Argentina (143,4%), Brazil (217.3%) and Mexico (172.1%). The technological effect is the main explanatory driver for this tendency compensating the negative effect from an unfavorable initial specialization (Brazil) and from a wrong direction of the technological efforts in relation to the direction of the technological opportunity (cases of Argentina and Mexico). Asian countries show extraordinary high rates of growth in their patent shares (competences) when compared to the Latin American ones, excluding Hong-Kong. The total effect in Hong-Kong shows that the country practically did not alter their share of patents in the world. China, South Korea and India registered the highest performances with four-digit rates of growth, followed with similar performance by Singapore and Taiwan. As in the Latin American case, most of the Total Effect is explained by the Technological Effect, this is, by own technological efforts. The Structural Effect is insignificant or even negative (China, India and Singapore). The initial unfavouravel distribution of competences was not a constraint to limit the possibilities of technological growth in any country along the decades. Nevertheless, and in opposition to Latin American, the adaptation effect, even being small but higher than the structural effect, is positive in all Asian countries -excepting India-. This result means that the technological efforts to build competences were in the 'correct' direction, this is, Asian countries follow the same direction pointed by opportunity and pervasiveness.

Table 2. –Shift-share analysis and Pearson Correlation.

	Technological Effect	Structural Effect	Adaptation Effect	Total Effect	Pearson Correlations		
	$s_{ij}^{t-1}\dot{c}_{ij}$	$s_{ij}^{t-1}\dot{o}_{ij}$	$s_{ij}^{t-1}\dot{c}_{ij}\dot{o}_{i}$	$\dot{c}_{j}$	(1)	(2)	(3)
Argentina	1,444	0,019	-0,029	1,434	0,420	-0,029	-0,079
Brazil	2,558	-0,016	-0,369	2,173	0,607	-0,183	0,057
Mexico	1,876	0,003	-0,158	1,721	0,500	-0,113	-0,231
Hong Kong	0,262	0,126	-0,133	0,255	0,470	-0,347	-0,101
Singapore	10,387	-0,014	0,517	10,890	0,354	0,103	0,323
Taiwan	5,670	0,062	0,632	6,364	0,173	0,048	0,229
South Korea	32,935	0,104	5,052	38,092	0,088	-0,002	0,180
China	24,378	-0,004	4,717	29,091	0,746	0,246	0,918
India	8,341	-0,055	-0,578	7,708	-0,070	0,028	0,347

(1) Correlation between the rate of growth of technology share and Technological Effect
(2) Correlation between the rate of growth of technology share and Structural Effect
(3) Correlation between the rate of growth of technology share and Adaptation Effect
Source: EPO, Space Bulletin 1978-2010 and own elaboration.

Pearson correlations confirms the above results. The correlation between the growth of technology share and the Technological Effect by technology is positive and significant in most of the countries. Taiwan and South Korea show also positive but low correlations, which means low association between the direction of national efforts and the highest rates of patent-growth. Only in the case of India, the correlation becomes negative.

Alternatively, the correlation between the growth of technology share and the Structural Effect by technology is low and negative in all American countries, Hong-Kong and South Korea. That result points out that there was no technological determinism. Unfavourable initial positioning in these countries was not a constraint to increase their technological share. For countries that show positive values, the correlations are not significant, excepting maybe in the case of China where the taking of advantages of their initial specialization looks to be higher.

The final correlation between the rate of growth of technology share and the adaptation effect show a clear pattern between Latin American countries plus Hong Kong and the rest of the Asian countries. The former group present negative correlations, which means that the national efforts were concentrated on technologies that did not follow the correct direction defined by technological opportunity. In opposition, the latter group present positive correlation, which is an evidence that the success of Asian countries for catching up was due to a concentration of the technological efforts following the direction of the technological dynamism. The values vary across countries. It is worth noting the correlation value for China (0,91).

To analyze the role of technological opportunity and cumulativeness on mobility, two indicators of mobility are defined considering the way countries build capabilities. To do that, technological competences are classified as core, niche, background or marginal (Patel and Pavitt, 1997). Core competences represent technological strengths and marginal competences represent technological shortcomings. Both, niche and background competences, represent the potential and the natural trend of technological growth. Niche competences explore technological niches from previous cumulative knowledge and background competences allow the exploration of new technological opportunities by using developed absorptive capacity to catch up. Under those considerations, "mobility by continuity" happens when core competences in the final period come from background or niche competences in the initial period; o when niche come from background (or vice versa). However, when countries built core, niche or background competences (final period) from marginal competences (initial period) is because they acquired the ability to make a technological leap by taking the advantages of "windows of opportunity". This is the case of "mobility by discontinuity". Formally, the variables are vectors that takes the following values:

$$M_j^c = \begin{cases} \dot{c}_{cj}, & c; number\ of\ technical\ fields\ with\ mobility\ by\ continuity \\ & 0, otherwise \end{cases}$$

$$M_j^D = \begin{cases} \dot{c}_{dj}, & d; number\ of\ technical\ fields\ with\ mobility\ by\ discontinuity \\ & 0, otherwise \end{cases}$$

As $\dot{c}_{cj}$ and $\dot{c}_{dj}$ are subsets of $\dot{c}_{ij}$, the contribution of mobility by continuity ($\widehat{M}_j^c$) and of mobility by discontinuity to growth ($\widehat{M}_j^d$) by country can be calculated using the technological effect as follows:

$$\widehat{M}_j^C = {}^1/_{\dot{c}_j} \sum_i s_{ij}^{t-1} \dot{c}_{cj}$$

$$\widehat{M}_j^D = {}^1/_{\dot{c}_j} \sum_i s_{ij}^{t-1} \dot{c}_{dj}$$

As presented in table 3, the contribution of mobility by discontinuity is much more significant than the contribution of mobility by continuity. That means that most of the growth of the world competences share is due to the building of new capabilities, and not from the old ones. All countries, without exception, took advantages from the 'windows of opportunity' opened by the new technological paradigms and by the market integration and made a technological leap. The highest contributions are registered in Hong-Kong (54%); China (43%) and Taiwan (40%). The contribution of mobility by continuity is much less significant, being higher in Singapore (20%) and Mexico (17%). In Argentina, Taiwan, South Korea and China, there were no mobility across competences by continuity at all. The question that remains is: In which technologies countries made the technological leap?. To answer that question, the mobility indicators were correlated with the national technological performance measured by the Total Effect ($\dot{c}_j$) and with the indicator of technological opportunity and pervasiveness ($\dot{o}_i$). Pearson correlations show that mobility by continuity is associated neither with the direction and intensity of national technical efforts [excepting in Singapore] nor with the direction of the technological opportunity [which is always negatively associated with] (Table 3). In opposite, mobility by discontinuity is quite highly associated with the direction and the intensity of technology efforts. The highest values are reached by China (0,94) and Brazil (0,67). Mexico (0,10), Hong-Kong (0,18) and Argentina (0,26) present the lowest correlation. The association between mobility by discontinuity and technological opportunity show a clear difference between both, Latin American and Asian countries. In Latin American countries, the technological leap did not follow the direction of technological opportunity and pervasiveness, so the Pearson correlations are negative or very low. Nevertheless, Asian countries show positive and quite high correlations [China (0,75); India (0,72); Taiwan (0,56)], which means that the technological leap happened on the most dynamic and pervasive technologies. This is the main difference between both groups of countries.

Table 3. – The association between mobility and cumulativeness (by continuity) versus mobility and opportunity (by discontinuity).

Pearson Correlations

	Mobility by continuity		Mobility by Discontinuity		Contribution of mobility to tech. performance	
	$\dot{c}_j$	$\dot{o}_i$	$\dot{c}_j$	$\dot{o}_i$	$\widehat{M}_j^C$	$\widehat{M}_j^D$
Argentina	-	-	0,26	-0,03	0,00	0,26
Brazil	0,19	-0,15	0,67	0,06	0,11	0,34
Mexico	0,11	-0,17	0,10	-0,13	0,17	0,29
Hong Kong	-0,04	-0,29	0,18	-0,18	0,06	0,54
Singapore	0,37	0,00	0,36	0,46	0,20	0,26
Taiwan	-	-	0,50	0,56	0,00	0,40
South Korea	-	-	0,42	0,35	0,00	0,29
China	-	-	0,94	0,72	0,00	0,43
India	0,01	-0,17	0,25	0,75	0,04	0,23

4.2. Persistence and Stability.

Stability of TSP is linked to the persistence of specific specializations (and despecializations) as the learning processes and knowledge accumulation are path-dependent. There are several measures of persistence in de literature according to the used definition. In this work, we will estimate three procedures to measure persistence. First one came from the definition of persistence at the firm level as "the conditional probability that innovators at time t will innovate at time t+1" (Malerba et al., 1997:804). Therefore, persistence at national level is the conditional probability of maintaining the specialization in period t at time t+1. This implies to assume that once a technological capability is achieved, it will keep stable.

The measure most widely used for specialization is the 'Normalized Revealed Technological Advantage' (NRTA) defined as $NRTA_j = {}^{(RTA_j - 1)}\big/_{(RTA_j + 1)}$, where $RTA_j = {}^{c_{ij}}\big/_{o_i}$. NRTA varies between [-1, 1]; [-1,0) values indicates despecialization and (0, 1] indicates specialization. Using NRTA, the measure of 'persistence in specialization' (P^S) is formally as follows:

$$P_s = P\left(NRTA_j^{t+1} > 0 \mid NRTA_j^t > 0 \right) = \frac{P(NRTA_j^t > 0 \cap NRTA_j^{t+1} > 0)}{P(NRTA_j^t > 0)}$$

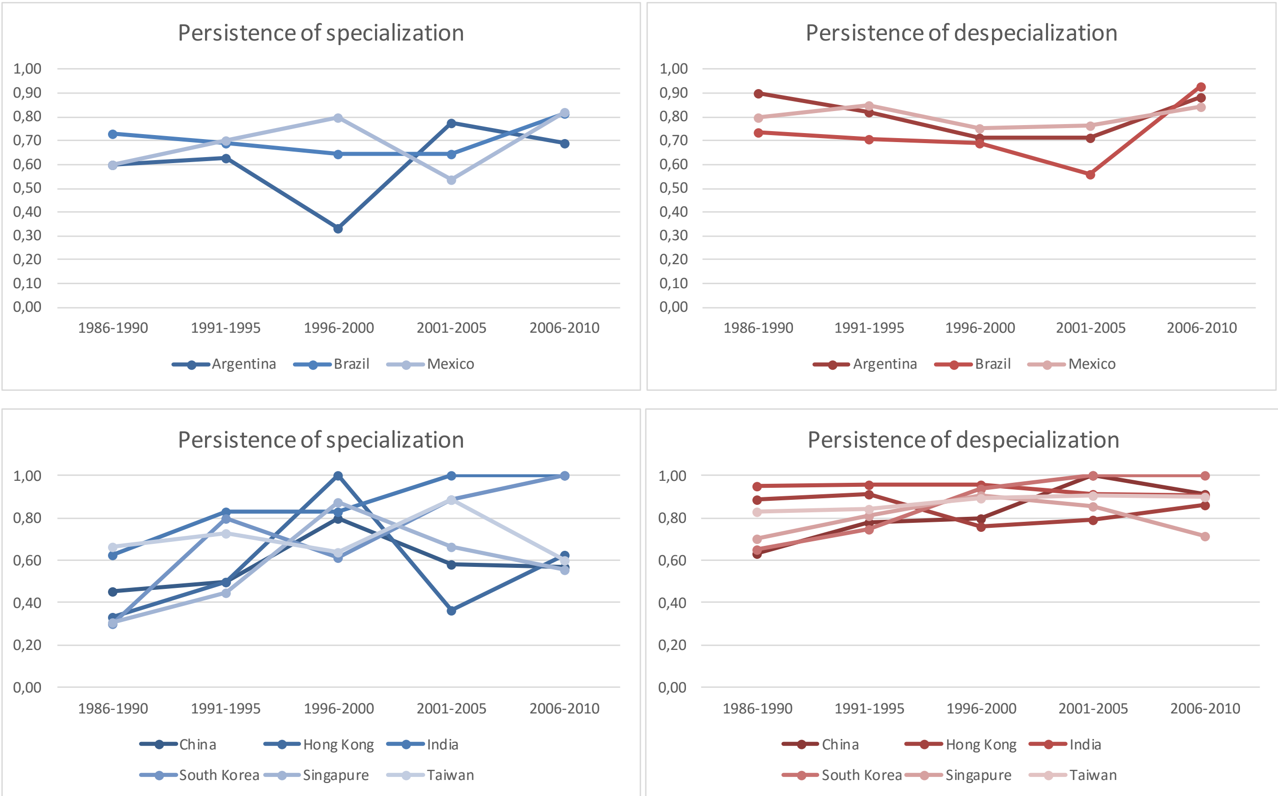
Second is 'persistence in despecialization' (SD), which measures the conditional probability of not be specialized in t given that the country was de-specialized in t-1.Formally,

$$P_D = P\left(NRTA_j^{t+1} < 0 \mid NRTA_j^t < 0 \right) = \frac{P(NRTA_j^t < 0 \cap NRTA_j^{t+1} < 0)}{P(NRTA_j^t < 0)}$$

A probability close to value 1 means stabilization of the TSP, while values moving away from one points out turbulence. All probabilities were calculated for a level of aggregation of 30 technical fields according to FISIR classification.

If the previsions about cumulativeness are correct, the probability to persist in des-specialization should be stable along time due to the difficulty to create new competences and capabilities from no previous relevant efforts. Persistence in specialization usually follows the same pattern of stability. Nevertheless, in developing countries, the stages of technological development are not still mature and some turbulence in specialization is expected. Along with the process of building of capabilities, some competences can have been created randomly and will not persist. In addition, spillovers and synergies among technology systems stimulate some mobility when specialization pushes the development of new competences in linked technologies.

Graph 1. Persistence in technological specialization and des-specialization in Asian and Latin American countries[1].



[1]: Measured as a probability. Values in vertical axis vary between 0 and 1.

Source: EPO, Space Bulletin 1978-2010 and own elaboration.

Graph 1 reports the evolution of P_S and P_D. Asian countries show a trend to stabilize their specializations until the final nineties going toward value 1. India and South Korea went ahead in this trend reaching value 1 in the two thousand. Nevertheless, China, Hong-Kog, Singapore and Taiwan revert de stabilization pattern, moving away from the value 1 along the last decade. Latin American countries follow a similar path, even they achieve lower values for the probability to persist in their specializations. Brazil trends to stabilize their specializations after a short period of turbulence in nineties. Mexico shows the same evolution, but with a higher level of turbulence in the nineties. Argentina shows the highest instability, which indicates a slower process of building of competences.

In general, persistence of despecialization is higher than the persistence of specialization, as theoretically expected. That means that the difficulty to create new competences in technical fields with no previous innovation efforts is high. The cumulative effect of learning allows creating new competences in technical fields related to previous capabilities along specific trajectories of technological diversification. As the distribution of competences is country-specific, the path of technological diversification depends on the specific bases of knowledge and their associated technological trajectories. The stability of despecialization patterns is more similar among the countries, although in general is higher in Asia than in Latin America. All the Asian countries reached value 1 or values quite close. Only Singapore moved away timidly at the final two thousands.

The second definition for persistence as "the degree of serial correlation in innovative activities" Malerba et al., 1997:804) inspired a second indicator: the Pearson correlation coefficient between the NRTA between two consecutive periods (Pavitt 1989; Brusoni and Geuna, 2003). A positive and significant Pearson coefficient would confirm the cumulativeness as the main explicative factor of stability of TPS throughout time. Results reported in table 3 do not reveal strong differences between Latin America and Asia in the stability of their TSP. At the initial periods, correlations are low (even negative in Singapore and China) which indicates some turbulence. But during the nineties and first two thousands, the TSP trend to stability reaching values between 0,7-0,9. Argentina and Hong Kong display a moderate turbulence in all periods.

Table 4.- Pearson Correlation of RTA values between t and t-1

Pearson Correlations

	1986-1990	1991-1995	1996-2000	2001-2005	2006-2010
Argentina	0,422	0,364	0,321	0,696	0,541
Brazil	0,545	0,421	0,656	0,683	0,811
Mexico	0,589	0,707	0,665	0,729	0,825
Hong Kong	0,449	0,635	0,610	0,193	0,425
Singapure	-0,057	0,466	0,723	0,741	0,839
Taiwan	0,495	0,555	0,590	0,807	0,766
South Korea	0,328	0,653	0,722	0,861	0,957
China	-0,222	0,177	0,288	0,762	0,911
India	0,665	0,759	0,685	0,915	0,935

Source: EPO, Space Bulletin 1978-2010 and own elaboration.

Finally, the third measure is the parameter (β) obtained by regressing the distribution of symmetric specialization index values across the i-technologies in the final period (S_{ij}^{t+1}) on the initial period (S_{ij}^{t}) by j-country, as follows:

$$S_{ij}^{t+1} = \alpha_i + \beta_i S_{ij}^{t} + \epsilon_i$$

A β coefficient equal to 1 means that the TSP remained unchanged over the period. A β coefficient between 0 and 1 means that the country decreased its des-specialization in technical fields where it was negatively specialized at the beginning of the period (or decreased its positive specialization where it was positively specialized). A β coefficient not significantly different from 0 indicates high turbulence, which allows rejecting the hypothesis that changes in specialization are cumulative. A β coefficient inferior to 0 points a reversion in the pattern of specialization. A β coefficient superior to 1 indicates that the TSP is increasing its positive specialization in technical fields where the country was already specialized (Cantwell 1989; Dalum et al. 1998; Laursen 1998). Nevertheless, a β coefficient superior to1 is not a necessary condition for increasing specialization (Cantwell, 1989). Instead of β, Dalum et al. (1998) proposed the S-specialization index calculated as β*/R*, being R* the correlation coefficient from the regression. S-specialization measures an increase or a fall in dispersion of specialization levels between two periods (Laursen 1998). If S-specialization is superior to one, specialization levels increased between periods. Otherwise, specialization decreased if S-specialization is lower than one. The dispersion of a given distribution does not change if S-specialization is equal to one.

Table 4.- Specialization and Dispersion: β and S-specialization indicators.

Pooled Data

	Argentina	Brazil	Mexico	China	Hong Kong	India	Singapore	South Korea	Taiwan
β	0,4353	0,6262	1,0986	0,2248	0,7953	1,5786	0,8059	0,7581	0,9992
t	6.22	9.58	18.53	3.19	14.67	30.71	15.68	13.98	15.01
P-value	0.000	0.000	0.000	0.002	0.000	0.000	0.000	0.000	0.000
S-specialization	2,156	1,655	1,577	3,869	1,348	1,828	1,296	1,339	1,663
Adjusted R^2	0,2019	0,3784	0,6967	0,0581	0,5898	0,8634	0,6217	0,5662	0,6010
F-Statisitic	38.70	91.72	343.30	10.20	215.24	942.91	245.85	195.45	225.44
Std Error	.0699717	.0653856	.0592932	.0703855	.0542123	.0514097	.0513956	.0542239	.0665498
β-specialization	Decrease specialization	Decrease specialization	Unchange	High Turbulence	Decrease specialization	Increase specialization	Decrease specialization	Decrease specialization	Unchange
S-specialization	Increase dispersion	Increase dispersion	Increase dispersion (low)	Increase dispersion	Increase dispersion (low)	Increase dispersion	Increase dispersion (low)	Increase dispersion	Increase dispersion

Source: EPO, Space Bulletin 1978-2010 and own elaboration.

Table 4 displays the results of β-parameter and S-specialization indicators. The β-parameter is always significant and only higher than one in Mexico and India. For the rest of the countries β-parameter is lower than one. That means that, in general, countries increased the NRTA values in the technologies they were initially despecialized or decreased the NRTA values in the technologies they were specialized. China presents the highest turbulence with a β-parameter quite close to zero (0.224). Mexico and Taiwan do not show significant changes. S-specialization is superior to one in all the countries, which reveals that all of them increased the dispersion of their NRTA. Changes in the dispersion of TSP was quite more relevant in China and Argentina. There are no relevant differences across the rest of countries.

4. Concluding remarks.

Technological opportunity and cumulativeness are elements that compose the technological regimes and both determine the path and trajectories of technical progress. The theoretical previsions about how both alter TSP is ambiguous. As learning and innovation are path dependent processes, both are associated to some kind of persistence. In addition, as knowledge is transversal, the technological systems as connected and both may represent ways to mobility. In this sense, this paper aimed to find some empirical evidence about how both contributed to the evolution of TSP in developing countries, where the process of building of capabilities is less mature and stable than in industrialized countries.

The decomposition of the growth of the technology share by country showed that in scenarios of a certain technological turbulence, with new emerging techno-economic paradigms and internationalization of products, firms and technologies, the paths of technical change could revert. Initial bad positioning by specialization in stagnant technologies is not a constraint to increase the world technology share or to move towards more dynamic technologies and go through open 'windows of opportunity'. Shift-share and Pearson correlations also showed that there are three main differences between Asian and Latin American countries. First, although the Latin American performed a good technological dynamism, the Asian (excluding Hong Kong) present a much more patenting activity, which is quite related to the incentives given by appropriate institutional frameworks and public policies. Second, Asian countries extended their technological bases to a broad set of dynamic but also stagnant technologies. The catching up process diversified the TSP by the complementary of efforts in a set of technology systems. That was especially relevant in South Korea, India, China and Singapore. Alternatively, Latin American countries increased the technology share in some technologies but also lost share in others. The catching up specialized the TSP by substitutability of efforts from some technologies to others. Third, Asian countries focused their technological effort in the direction of the more dynamic technologies coming from the emerging paradigms in eighties (semiconductors, telecommunications, audiovisual, electronics). Meanwhile, Latin American moved also to some dynamic technologies, but not related with the emerging techno-economic paradigms. This means that catching up did not take the advantages of the windows of opportunity opened by that new technologies.

Persistence analysis used three measures: the probability to persist along the period, the Pearson correlation index between two consecutive distributions of specialization index and the β and S-specialization indexes. All measures confirmed an initial turbulence subsequently overcome, that is, a general trend to stability, but with some qualifications. Persistence of despecialization is higher and more stable in Asian countries than in Latin American countries. Persistence of specialization has a different timing in the two groups. In the Latin American, there is a period of instability in the middle of the nineties, while in the Asian that happens in the first two thousands, except for India and South Korea that stand the stabilization trend. After the period of turbulence, Latin American countries trend to stabilization rapidly while Asian countries remain with some level of instability.

Correlation index allows evaluating if the intensity of the specialization remains between consecutive periods. At the initial periods, turbulence is higher and the specialization values between consecutive periods are not correlated. However, as time passes and TSP stabilize, the specialization values trend to remain and correlation indexes become higher. That is clearly an effect of cumulativness. Finally, β and S-specialization indicators allows to characterize the catching up in the selected group of developing countries as a process that diminished the dispersion of high values for specialization and despecialization, as well as allowed the countries to consolidate the specializations achieved in the process of creation of competences and capabilities.

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