Are technological specialization patterns random or cumulative in East Asia? An analysis of patent statistics

東アジア経済の技術特化パターンはランダムか累積的か？特許データを用いた実証分析

Kazuhiro Miyagi*
宮 城　和 宏

要約

近年、東アジアのイノベーション能力が向上してきたにもかかわらず、特許データを用いた技術イノベーションの実態について実証的に明らかにしてきた研究はこれまでほとんどみられない。本稿では、東アジア各国の技術特化パターンに焦点を当て、①各国の違いあるいは類似性、②東アジア各国の技術特化パターンは未だにランダムなのか、それとも過去の技術蓄積を反映して累積的なパターンへ移行したのか等について東アジアの10カ国･地域（日本、韓国、台湾、シンガポール、香港、タイ、マレーシア、フィリピン、インドネシア、中国）を対象に米国特許商標庁（USPTO）の特許データを用いた統計学的な検証を行う。

ABSTRACT

Despite the increase in the technological capabilities of the East Asian economies there has been little quantitative research regarding the dynamic changes in their technological specialization patterns. This paper statistically investigates the following questions using patent data. (1) Are the technological specialization patterns of the East Asian economies analogous, or do they differ? (2) Are the technological specialization patterns in East Asia path dependent or cumulative reflecting prior learning or technological accumulation, or alternatively, are they stuck in random patterns? (3) Does the incremental process of technological specialization cause shifts in the sectoral composition of innovation in the long term? Empirical analysis confirms that many of the East Asian economies moved from random patterns of technological specialization to patterns of specialization which are cumulative and incremental, and that this was accompanied by a decrease in the degree of technological specialization.

* Professor, Department of Economics, Okinawa International University.
E-mail address: kazuhirom@okiu.ac.jp
沖縄国際大学経済学部教授
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1. Introduction

Technology possesses properties which are firm-specific and tacit, to a large extent embodied in individuals or institutions, in addition to being cumulative (Rosenberg, 1982, Pavitt, 1988, Arthur, 1988). When firms select technology, they do not have a complete stock of knowledge which can be referred to, and upgrade technology using learning through experience and by trial-and-error with previously accumulated technology as a basis. They make efforts to diversify technology, and construct an existing technology base. It is misleading to assume that the acquisition of technology through this kind of learning is random, or that it is a purely costless by-product along the lines of learning-by-doing or learning-by-using activities (Patel and Pavitt, 1994, Pavitt, 1988).

As industrial technologies grow increasingly complex, regardless of whether they are tacit or codified and explicit, the necessary knowledge and skills have become largely specific to particular categories of industry, products and processes. As a result, the technologies accumulated through each of the activities of product design, production engineering, quality control, education and training, research, or the development and testing of prototypes, can be thought of as being differentiated by the specialized patterns reflecting the content of each learning process (Bell and Pavitt, 1997). That is to say, as a result of the specific directions in which technological changes are lead by previous learning, differences among countries in the resources devoted to such deliberate learning or technological accumulation have led to international differences in technological specialization pattern. Previously established technological specialization patterns are therefore mutually stable, and there is a high likelihood that the sectors in which each country is technologically strongest only change gradually (Pavitt, 1988).

However, the cumulative nature of technological learning does not imply that technological changes are always incremental. The majority of technological changes occur through continuous incremental change, but there are also clearly distinguishable discontinuities due to radical changes in the core technologies of processes and products (Tsuman and Anderson, 1986), in architectures (Henderson and Clark, 1990) and so on. In these cases, it may be that firms are able to move into new areas through the use of linkages or networks to draw on new bodies of knowledge complementing their existing areas of technological competence or from a wealthy knowledge base already accumulated through predictions regarding discontinuities. Alternatively, new entries may deliver discontinuities, but even in this case it may also be thought that such firms are moving along their own cumulative learning paths in a new field of knowledge (Bell and Pavitt, 1997).

Cumulative characteristics of technology give rise to the following three propositions regarding countries' technological specialization patterns. (1) Each country's technological specialization pattern reflects past learning or accumulated technology, and each is different. (2) The majority of technological changes are cumulative or path-dependent processes, and the patterns of technological specialization are stable for a fixed period of time[1]. (3) Technological change is an incremental process, and the sectoral composition of innovation may shift in the long term.

The investigation of these propositions has mainly been conducted with respect to the developed countries of Europe and the United States. For example, the differences in technological specialization patterns have been made clear for the OECD nations by Pavitt

(1988), Cantwell (1989), Patel and Pavitt (1994), Archibugi and Pianta (1992, 1994), and also for Asia by Choung (1998), Mahmood and Sing (2003), Huang and Miozzo (2004) and Miyagi (2006). Dynamic changes, including the proposition regarding the cumulative nature of technological specialization patterns, have been statistically investigated for the OECD countries by Archibugi and Pianta (1992), Patel and Pavitt (1994), Cantwell (1989) and Laursen (2000), who each used different methods. These results confirmed that the path of technological development differs in each country, and aside from Laursen (2000), that the degree of technological specialization generally increases for most countries, that is, it is cumulative.

The point of note is that, regardless of the recent expansion in innovative capabilities exemplified by the rapid increase in the number of patents in East Asian NIEs such as South Korea and Taiwan, there has been absolutely no research regarding dynamic changes in technological specialization patterns in East Asia[2]. In terms of the propositions above, there is almost no existing research that responds to inquiries such as (1) are the technological specialization patterns of the East Asian economies analogous, or do they differ? (2) Are the technological specialization patterns in East Asia stable due to path dependent patterns or cumulative patterns reflecting prior learning or technological accumulation? Or, are they stuck in random patterns under which the sectors of specialization periodically switch, without advancing the accumulation of technology? (3) Does the incremental process of technological specialization cause shifts in the sectoral composition of innovative sectors in the long term?

In order to respond to the inquiries above in this paper, a statistical investigation was conducted using U.S. Patent and Trademark Office (USPTO) patent data for 10 East Asian countries and regions (Japan, South Korea, Taiwan, Singapore, Hong Kong, Thailand, Malaysia, The Philippines, Indonesia and China). Section 2 presents a theoretical investigation, and the data used and analysis methods are explained in section 3. Next, in section 4 the results of analysis are discussed, and lastly the main conclusions are presented along with future work.

2. Empirical Analysis: Data and Methodology

2.1 Data

When conducting international comparisons of technological change and specialization using patent data, the potential difficulty is that the intellectual property rights (IPR) systems of different countries are strongly rooted historically and embedded in often very different institutional structures, which yields differences among countries in governance of patent systems (Andersen and Howells 2000)[3]. According to Soete (1987), Pavitt (1988), Cantwell (1989) and Andersen (2001), the U.S. is the economy with the most historically developed property rights system, and patents granted in the U.S. provide the most useful basis for international comparisons, given the common screening procedures imposed by the USPTO. Moreover, as the U.S. has historically been an economy with the largest and technologically most developed market in the world, and a country that explicitly encourages and welcomes new ideas and innovations, it is reasonable to assume that inventions with strong commercial expectations are patented there (Soete and Wayatt 1983, Archibugi and Pianta 1994, Andersen 2001). Consequently, data derived from patents granted in the U.S. provide the most useful indicator for identifying technological specialization.

In this study, the original data used for the calculation of all technological indices are from the USPTO database, in which the patented inventions are grouped in about 400 main (3-digit) patent classes, though the classification system actually contains thousands of subclasses. Even 400 classes are far too many for our analysis, and hence we use a higher-level technological classification developed by Hall et al. (2001), according to which the 400 classes are aggregated into 36 two-digit technological sub-categories, and these in turn are further aggregated into 6 main categories[4]. We divide the entire period of 43 years from 1963 to 2005 into four consecutive 10-year periods based on the grant year (1963 - 74, 1975 - 1984, 1985 - 1994, 1995 - 2005) in order to reduce the erratic year-to-year variation in the data (i.e., the number of patents per country and technology fields in each period is large enough to avoid large fluctuations in the values of indices)[5].

2.2 Methodology

In order to analyze intertemporal changes of technological specialization patterns, a method known as the Galtonian regression model, a statistical technique devised for the analysis of bivariate distributions, is used. This approach was first used in research concerning the size distribution of firms by Hart and Prais (1956), and other useful applications have since been developed by Hart (1976) in investigating changes in income distribution. Regarding changes in the distribution of technological specialization indices between two points in time, it was first applied to conduct similar analyses by Cantwell (1989), who focused on the developed countries of Europe and the U.S., and subsequently to the OECD countries by Archibugi and Pianta (1992), Dalum, Laursen and Villumsen (1998) and Laursen (2000ab).

2.2.1 Technological Specialization Index

The revealed comparative advantage index (Balassa, 1965) is a numerical reference by which to measure the specialization occurring in trade. This was first applied to technology by Soete (1987), and is known as the revealed technological advantage index (RTA) index. The RTA index for country i in sector j is defined as the ratio of country i's share of total world patents in sector j to country i's share of total world patents, i.e.

$$RTA_{ij} = \left(n_{ij} / \sum_i n_{ij}\right) \Big/ \left(\sum_j n_{ij} / \sum_i \sum_j n_{ij}\right) \tag{1}$$

Where n_{ij} is the number of patents of country i in sector j. By definition, if the country holds the same share of worldwide patents in a given technology as in the aggregate, this index equals 1, and is above (below) 1 if there is a relative strength (weakness). The RTA index has been used in much research attempting to reveal the technological specialization patterns in sectors, such as Soete (1987), Pavitt (1987), Patel and Pavitt (1994), Cantwell (1989), Archibugi and Pianta (1992), Choung (1998), Mahmood and Sing (2003), Huang and Miozzo (2004), Miyagi (2006) and so on. However, it is inappropriate to conduct regression analysis using this index when the absolute number of patents in an individual country is small. Firstly, when using patent data of developing countries, the small absolute number of patents yields the possibility that many sectors may have zero patents, particularly during the initial stages of development[6]. In such cases, the RTA index for the aforementioned sectors becomes 0. Secondly, this index has a weighted average equal to 1 and a skewed distribution, taking values between zero and infinity[7]. When patents have a large bias towards a specific sector it is easy for the distribution to become asymmetric, and the lack of tuning aimed at symmetry leads to a bias in results. To perform regression analysis, it is preferable to use a modified and symmetric version of this index.

In order to conquer the issue above, the value of the RTA index is modified and normalized as follows, according to Dalum et al. (1988) and Laursen (2000).

$$RSTA_{ij} = (RTA_{ij} - 1)/(RTA_{ij} + 1) \tag{2}$$

Equation (2) is known as the revealed symmetric technological advantage (RSTA) index, and takes a value between -1 and 1. When RTAij=0, RSTAij=−1, when RTAij=1, RSTAij=0 and when RTAij>1, the larger the value of RTAij, the closer RSTAij draws to 1. Thus, if RSTAij>0 then the country i is relatively specialized in sector j.

2.2.2 Galtonian Regression Model

According to the theory of technological accumulation, the distribution of the RSTA index is stable over the time. This means that when the RSTA index is compared over two periods of time, the distribution between two sectors of technological specialization has a positive correlation. However, when the nature of innovative activity changes gradually, the degree of correlation may deteriorate. The correlation between the distributions of RSTA indices for sectors during two periods is estimated by means of the following simple cross-section analysis.

$$RSTA_{ij}^{t2} = \alpha_i + \beta_i \, RSTA_{ij}^{t1} + \varepsilon_{ij}^{t2} \tag{3}$$

Where i represents a country (i = 1,........,10), j represents the sector of industry (j = 1,......,36), α and β are standard linear regression parameters, and ε is a residual term. The superscripts t1 and t2 refer to two different periods of time. The dependent variable, RSTAij at time t2 for sector i, is tested against the independent variable, which is the value of RSTAij in the previous time t1. In equation (3), the two most distant periods are first considered (t1: 1963 - 74, t2: 1995 - 2005), in order to capture the dynamic aspect of the changes in the RSTA. Consideration is then paid to the period 1975 - 85 with respect to 1995 - 2005, and lastly to the closest periods, 1985 - 94 with respect to 1995 - 2005.

β-specialization and Regression effect

The estimated results can be interpreted as follows. Firstly, $\hat{\beta} \geqq 1$ is the condition under which cumulativeness in the sectoral distribution of innovation outweigh incremental change[8]. Within this condition, if $\hat{\beta} = 1$ then the RSTA distributions for the two periods are perfectly cumulative, and there are no structural changes during the two periods. The ranking of the industrial sector therefore does not change. This not only means that technologically specialized and de-specialized sectors experience respectively no further specialization nor change in degree of minority, but also that they are each fixed in exactly the same position during the two periods. This proposition is investigated with $H_0 : \hat{\beta} = 1$. In the case that $\hat{\beta} > 1$ on the other hand, while the accumulation pattern is intensified and the specialized sectors are further enhanced, de-specialized sectors also become further subordinated. This has been termed β -specialization by analogy to the convergence literature of Barro and Sala-i-Martin (1991) among others (Dalum et al., 1998, Laursen, 2000).

The next case is that of $0 < \hat{\beta} < 1$, which represents a combination of incremental change and cumulativeness in the pattern of technological specialization. By the same analogy as above, this is termed β-de-specialization. In this case, while the specialized sectors recede, de-specialized sectors improve their position. This is what has been termed 'regression towards the mean' (Hart, 1976). As a consequence, $(1-\hat{\beta})$ becomes a measure of the size of the so-called 'regression effect', and an interpretation of the estimated coefficient β. That is to say, the closer β draws to zero, the larger the regression effect. However, it should be noted that the specialized and de-specialized sectors grow come closer to one another, but this does not mean that the relationship between them is reversed, and the actual ranking of each sector does not change. In addition, the test of whether $\hat{\beta}$ is significantly larger than zero ($\hat{\beta} > 0$) is a test of the properties of accumulation against the proposition that the sectoral composition of innovation is random (in this case, $\hat{\beta} = 0$). This is investigated using a t-test with respect to H_0 : $\beta = 0$.

Lastly, in the special case of $\hat{\beta} < 0$, the ranking of sectors is reversed at the 2 points in time, in opposition to the anticipated cumulativeness of technological specialization. Those RSTAs initially below the country average are above average in the final period and vice versa. If $\hat{\beta} \leqq 0$ then the hypothesis that a country's technological specialization pattern is reversed ($\hat{\beta} < 0$) or is random ($\hat{\beta} = 0$) cannot be rejected.

σ-specialization

The degree of technological specialization in a country can be measured by the variance of its RSTA index. Pavitt (1988) used the standard deviation of the RTA index as an indicator of such specialization. Soete's (1987) original work also analyzed the variance of the RTA index.

We follow the method of Hart (1976) to estimate the changes in the variance of the distribution. From equation (3), the variance σ^{2t2} of the RSTA index during period t2 may be expressed using the equation below.

$$\delta_i^{2t2} = \beta_i^2 \delta_i^{2t1} + \delta_\varepsilon^2 \tag{4}$$

Then, the square of the correlation coefficient (R^2) is given by

$$R_i^2 = 1 - \left(\delta_\varepsilon^2 / \delta_i^{2t2} \right) = \left(\delta_i^{2t2} - \delta_\varepsilon^2 \right) \left(1 / \delta_i^{2t2} \right) \tag{5}$$

Combining equations (4) and (5) it follows that:

$$\delta_i^{2t2} - \delta_\varepsilon^2 = \beta_i^2 \delta_i^{2t1} = R_i^2 \delta_i^{2t2} \tag{6}$$

Equation (6) may be transformed as below, in order to show the relationship between the variances of the two distributions.

$$\delta_i^{2t2} / \delta_i^{2t1} = \beta_i^2 / R_i^2 \tag{7}$$

From equation (7) it follows that:

$$\delta_i^{t2} / \delta_i^{t1} = \left| \beta_i / R_i \right| \tag{8}$$

From equation (7), it can be seen that the degree of technological specialization increases in the case that $\beta^2 > R^2$, and decreases in the case that $\beta^2 < R^2$. A high variance indicates a high or narrow degree of technological specialization, and a low variance indicates that the country has either a broad range or low degree of technological advantages[9]. If the values of the estimated coefficient of regression is used, the degree of specialization rises where $|\hat{\beta}| > |\hat{R}|$ (equivalent to an increase in the variance), and falls where $|\hat{\beta}| < |\hat{R}|$ (equivalent to a decrease in the variance). Further, in the case that $|\hat{\beta}| = |\hat{R}|$, the degree of specialization does not change. Of these cases, $|\hat{\beta}| > |\hat{R}|$ may be referred to as σ-specialization by analogy with the convergence literature, and $|\hat{\beta}| < |\hat{R}|$ may be referred to as σ-de-specialization (Dalum et al., 1998, Laursen, 1990ab).

Mobility Effect

The estimated Pearson correlation coefficient $\hat{R}$ is a measure of the mobility of sectors up and down the RSTA distribution. A high value of $\hat{R}$ indicates that there is little change in the relative positions of the sectors, and a low value of $\hat{R}$ on the other hand, indicates that some sectors are moving closer together and others further apart, quite possible to the extent that the ranking of sectors changes. Here, the size of $(1-\hat{R})$ thus measures, the so-called 'mobility effect', and a large mobility effect means that the ranking among sectors changes. It may well be that, even where the regression effects $(1-\beta)$ suggests a fall in the degree of technological specialization due to a proportional move in sectors towards the average ($\beta<1$), this is outweighed by the mobility effect $(1-R)$, due to changes in the proportional position between sectors ($\beta>R$). Thus, we can characterize a decrease in the dispersion as a change towards a more 'broad' pattern, and an increase in the dispersion as a change towards a more 'narrow' specialization pattern.

3. Estimation Results

3.1 Technological Specialization Patterns, Country Size and Development Level

It has been observed that the degree of a country's technological specialization is influenced by the size of the country and its level of development. For example, Pavitt (1988) made it clear by analyzing the variance of the RTA index that while large industrial countries such as the U.S. and Japan possess a broad range of technological specialization, the range of specialization is narrowest in small industrial countries like Sweden, Switzerland and Belgium. Also, by analyzing the standard deviation of the RSTA for the OECD countries, Laursen (2000) made it clear that small countries are more specialized than large countries, and that if the size of countries is treated as a given then Greece, Spain and Portugal, which have a relatively low development level, are more specialized than other countries.

Table 1 shows the same index for 10 countries in East Asia. The following characteristics can be seen in the relationship between the degree of specialization for countries in terms of the standard deviation of the RSTA over the period 1995 - 2005, the sizes of the countries and the per capita GDP. Firstly, the degree of specialization is low for large countries like Japan and China, but comparatively high for small countries such as Hong Kong and Singapore. However, for countries like Indonesia, which has the lowest per capita GDP, even though the size may be large, the degree of specialization is the highest in comparison to the other countries. It can be seen from the table that the specialization levels for Singapore and Hong Kong, which have a small size but high per capita GDP, are even lower those of Indonesia, the Philippines and Thailand, which have larger sizes but low levels of development.

3.2 Similarities and Differences among Economies in Sectoral Specialization

Table 2 shows an investigation of the correlation among the technological specialization patterns for each country using RSTA indices composed from 36 sectors, for the period 1995 - 2005. It can be seen that among the total of 45 pairs, 10 pairs (22%) have significant positive correlations. Singapore and Malaysia have the most, each having 4 pairs which are positive with a significant correlation. In contrast, Thailand and China have absolutely no significant correlation with other countries. It is interesting to note that Japan and South Korea have the highest correlation of 0.725. The technological specialization pattern of the two countries is very similar, and it can be seen that they are in a competitive relationship from a technological perspective. Japan also has the most negative correlations with the other countries, with 6 such correlations. It only has significant positive correlations with South Korea and Singapore, and it can be seen that Japan has a complementary technological relationship with the other countries in East Asia.

Table 1. The standard deviation for technological specialization patterns 1995 - 2005 for 10 East Asian economies in descending order(n = 36 sectors)

	S.D.	Population (milllions, 2004)	GDP per capita US dollars (PPP), 2004
Indonesia	0.648	222.6	3,622
Pillippines	0.549	81.4	4,561
Thailand	0.410	63.5	7,901
Hong-Kong	0.388	7.1	30,558
Singapore	0.388	4.3	26,799
Taiwan	0.380	22.5	25,614
Korea	0.360	48	21,305
Malaysia	0.352	24.9	10,423
Japan	0.288	127.8	29,906
China	0.244	1,313.3	5,642

Note: For a description of the 36 sectors, see Hall et al.(2001)
Source: for S.D., caluculation by author, for Population and GDP per capita, World Economic Forum(2005)

Table 2. Correlations of RSTA Indices across 36 Sectors: 1995 - 2005

	Indonesia	Thailand	Malaysia	Hong Kong	China	Singapore	Philippines	Korea	Taiwan	Japan
Indonesia	1.000									
Thailand	0.039	1.000								
Malaysia	0.017	0.252	1.000							
Hong Kong	0.013	0.161	0.332*	1.000						
China	0.067	0.010	0.019	0.212	1.000					
Singapore	-0.012	-0.141	0.380*	-0.047	-0.167	1.000				
Philippines	0.430**	0.242	0.500**	0.140	0.139	0.395*	1.000			
Korea	-0.195	-0.406	0.012	0.092	0.077	0.427**	0.003	1.000		
Taiwan	0.061	0.230	0.508**	0.706**	0.118	0.266	0.285	0.269	1.000	
Japan	-0.417*	-0.379*	-0.029	-0.057	-0.086	0.400*	-0.179	0.725**	0.201	1.000

** denotes correlation coefficient significantly different from zero at the 1% level.
* denotes correlation coefficient significantly different from zero at the 5% level.
Source: Based on data by the USPTO.

Patel and Pavitt (1994) conducted a similar analysis focused on the OECD countries' RTA indices (over 34 sectors) for the period 1985 - 90. The results made it clear that of 171 pairs, only 31 (18%) had positive correlations significant at the 5% level, and that Japan had a unique specialization pattern with no positive correlation with any other country, and many negative correlations. These results reveal that in general, there is a striking tendency for countries to take on different patterns of technological specialization, and it has been concluded that this reflects the inevitable diversification in stages of economic and technological development, or a desirable diversity in fields of scientific and technological specialization.

The ratio of correlated pairs among the 10 East Asian countries (22%) which confirms a significant positive correlation is slightly higher than the correlation ratio among the OECD countries (18%) reported by Patel and Pavitt (1994). As a fraction of the whole however, this is less than a quarter so the technological specialization patterns of the East Asian countries may be regarded as different in most cases.

3.3 Dynamic Aspects of Changes in Technological Specialization Patterns

Table 3 shows the estimated results of regression of the RSTA index in 1995 - 2005 on the index in 1963 - 74 for each country. Firstly, regarding the periods 1963 - 74 and 1995 - 2005, apart from Japan and Hong Kong, the null hypothesis H_0 : $\beta=0$ cannot be rejected. That is to say, for all the countries excluding Japan and Hong Kong, cumulativeness cannot be recognized in the technological specialization patterns in both 1963 - 74 and 1995 - 2005, and the changes in the specialization patterns are random. In part, this result may reflect the absolutely small number of those countries' patents granted in the US except Japan and Hong Kong, despite counting over a long period of 12 years from 1963 - 1974. That is, throughout the 1960s and first half of the 1970s a technological accumulation pattern was not formed in any but these two countries. On the other hand, for Japan $\hat{\beta}=0.647$, and Hong Kong $\hat{\beta}=0.383$, it is revealed that there were already cumulative and incremental technological specialization patterns at this point in time (β-de-specialization). In addition, the hypothesis of a cumulative and path-dependent technological specialization pattern (H_0 : $\beta=1$) is rejected for all countries. That is to say, there are no countries for which the specialization pattern of 1963 - 74 continues unchanged. Regarding the change in degree of technological specialization, Taiwan and Indonesia are the only cases for which $\hat{\beta}/\hat{R}>1$ and the degree of specialization is increasing (σ-specialization). For the remaining 8 countries $\hat{\beta}/\hat{R}<1$ and the degree of specialization is decreasing (σ-de-specialization). This results show that the number of the countries' patents in the US apart from Taiwan and Indonesia has a tendency to expand the range of the corresponding sectors. In part, this reflects the fact that there was a rapid increase in patenting in the U.S. in a broad range of sectors during the period 1995 - 2005 with respect to the period 1963 - 74.

Table 3. The development of technological specialization patterns 1963 - 2005 for 10 East Asian economies (n=36sectors)

	1963 - 74 to 1995 - 05			
	$\hat{\beta}$	$\hat{\beta}/\hat{R}$	(1-$\hat{\beta}$)	(1-$\hat{R}$)
Japan	0.647**##	0.94	0.35	0.31
Taiwan	0.119##	1.25	0.88	0.91
Hong Kong	0.383**##	0.67	0.62	0.43
Korea	-0.114##	0.57	1.11	1.20
Singapore	-0.087##	0.58	1.09	1.15

China	$0.047^{\#\#}$	0.47	0.95	0.90
Malaysia	$0.126^{\#\#}$	0.75	0.87	0.83
Thailand	$0.044^{\#\#}$	0.92	0.96	0.95
Philippines	$0.076^{\#\#}$	0.93	0.92	0.92
Indonesia	$-0.07^{\#\#}$	1.11	1.07	1.06

Note: The degree of specialization= $\hat{\beta}$ / $\hat{R}$, the regression effect = (1- $\hat{\beta}$), and the mobility effect = (1-$\hat{R}$).
** denotes significantly different from zero at the 1% level.
* denotes significantly different from zero at the 5% level.
denotes significantly different from unity at the 1% level.
# denotes significantly different from unity at the 5% level.

With respect to the periods 1975 - 84 and 1995 - 2005, the changes in the technological specialization patterns are as follows (Table 4). Firstly, following Japan, $\beta=0$ is also rejected at the 1% or 5% level for Taiwan, Hong Kong, Singapore and Indonesia, but may not be rejected for the remaining 5 countries (South Korea, China, Malaysia, Thailand and the Philippines). That is to say, while the technological specialization occurring in the two periods for the 5 remaining countries continues to retain the random pattern of the period 1963 - 74, Taiwan and Indonesia moves into a β-de-specialization pattern of cumulative and incremental change ($0<\hat{\beta}<1$) from 1975 - 84. On the other hand, although H_0 : $\beta=0$ is rejected at the 5% level only for Singapore, the value of $\hat{\beta}$ is $\hat{\beta}<0$ and the possibility that the technological specialization pattern of Singapore is reversed between the two periods is high, contrary to the hypothesis of cumulativeness. That is, the specialization patterns for the periods 1975 - 84 and 1995 - 2005 are very different. As we have seen in Table 1, Singapore is small country, and the degree of specialization is relatively high, despite its high level of per capita GDP. In addition, it is well known that Singapore has experienced TNC-led growth. Those may be the one of the reasons why Singapore had its reversed specialization pattern between the two periods.

Table 4. The development of technological specialization patterns 1975 - 2005 for 10 East Asian economies (n=36sectors)

	1975 - 84 to 1995 - 05			
	$\hat{\beta}$	$\hat{\beta}$ / $\hat{R}$	(1- $\hat{\beta}$)	(1-$\hat{R}$)
Japan	0.905^{**}	1.06	0.10	0.15
Taiwan	$0.498^{**\#\#}$	0.80	0.50	0.38
Hong Kong	$0.256^{*\#\#}$	0.68	0.74	0.63
Korea	$-0.096^{\#\#}$	0.79	1.10	1.12
Singapore	$-0.204^{*\#\#}$	0.57	1.20	1.36
China	$0.038^{\#\#}$	0.37	0.96	0.90
Malaysia	$0.047^{\#\#}$	0.55	0.95	0.91
Thailand	$0.122^{\#\#}$	0.68	0.88	0.82
Philippines	$0.026^{\#\#}$	0.90	0.97	0.97
Indonesia	$0.458^{*\#}$	1.28	0.54	0.64

Note: The degree of specialization= $\hat{\beta}$ / $\hat{R}$, the regression effect = (1- $\hat{\beta}$), and the mobility effect = (1-$\hat{R}$).
** denotes significantly different from zero at the 1% level.
* denotes significantly different from zero at the 5% level.
denotes significantly different from unity at the 1% level.
# denotes significantly different from unity at the 5% level.

Regarding the presence or absence of the path dependent specialization pattern indicated by Arthur (1988), $H_0: \beta = 1$ can be rejected in all cases except Japan. That is to say, the value of β for Japan is 0.905 and $0 < \hat{\beta} < 1$, but since this is close to 1 it could be said that rather than having a cumulative and incremental specialization pattern,the distributions of the RSTA index in the two periods indicate mostly identical cumulative and path-dependent specialization patterns.

This may be reconfirmed according to the fact that the value of $\hat{\beta} / \hat{R}$, which indicates the degree of technological specialization, is 1.06 for Japan, which is also quite close to 1. Regarding the degree of technological specialization in the other countries, only Indonesia has $\hat{\beta} / \hat{R} > 1$, indicating σ-specialization (a specialization pattern in which the degree of specialization increases or the range is narrowed), and the reverse, σ-de-specialization (a specialization pattern with a broad range), for the rest. The degree of technological specialization increases for all the countries apart from Indonesia, but in the same manner as the previously analyzed periods, this reflects the fact that patents increased across a broad range of sectors in the period 1995 - 2005 with respect to 1975 - 84. On the other hand, the number of patents for Indonesia during the period 1995 - 2005 was only 58 and the smallest over 10 countries, which reveals that patenting extended only to a small range of sectors. Also, in contrast to the fact that the mobility effect (which is measured by $1\text{-}\hat{R}$) exceeds the regression effect (which is measured by $\hat{\beta}$) in Indonesia, for Taiwan and Hong Kong, the opposite is true. This shows that the decrease in the degree of technological specialization in Taiwan and Hong Kong occurred in parallel with a stable pattern of technological specialization[10].

Finally, the results regarding the periods 1985 - 94 and 1995 - 2005 are as follows (Table 5). At this stage the hypothesis $H_0: \beta = 0$ is rejected at the 1% or 5% level in all cases except the Philippines. Entering these periods, only the Philippines still retains a random pattern of specialization, and a β-de-specialization pattern of cumulative and incremental specialization can be seen in all the other countries, showing a 'regression towards the mean'. However, for Japan alone, $H_0: \beta = 1$ cannot be rejected for these periods of analysis (1985 - 94 and 1995 - 2005). That is, for Japan, $\hat{\beta}$ is not significantly different from one (which amounts to a test on whether the regression effect, $1\text{-}\hat{\beta}$, is significantly different from zero). This reveals that since 1975 - 84 Japan has remained a cumulative and path-dependent technological specialization pattern. Also, the value of $\hat{\beta} / \hat{R}$ reflecting the degree of technological specialization is 1.02 for Japan, which is even closer to 1 than in the previous periods of analysis, that is, the variances of the two periods are almost equal, and it can be seen that the pattern of technological specialization has become fixed.

Regarding the change in the degree of technological specialization in the other countries for 8 of 9 countries, except Indonesia, the value of $\hat{\beta} / \hat{R}$ are smaller than 1, and the regression effect exceeds the mobility effect. This means that there has been a tendency for the degree of technological specialization to fall over the past 20 years (σ-de-specialization or broad specialization). Aside from Japan and Indonesia, in the remaining 8 countries the decrease in the degree of technological specialization reflects the fact that the number of patents increased across a broad range of sectors in the period 1995 - 2005 with respect to 1985 - 94. However, among the 8 countries for which the degree of specialization decreased, excluding Thailand and the Philippines, the values of $\hat{\beta} / \hat{R}$ for Taiwan, Hong Kong, South Korea, Singapore, China and Malaysia increased even more than for the previous periods of analysis (1975 - 84 and 1995 - 2005), from which it can be seen that the degree of technological specialization had an increasing tendency in these 6 countries. On the other hand, it can also be seen that there was even more of a decreasing tendency in the degree of specialization in Thailand and the Philippines.

Table 5. The development of technological specialization patterns 1985 - 2005 for 10 East Asian economies (n=36sectors)

	1985 - 94 to 1995 - 05			
	$\hat{\beta}$	$\hat{\beta}$ / $\hat{R}$	(1- $\hat{\beta}$)	(1-$\hat{R}$)
Japan	0.958**	1.02	0.04	0.06
Taiwan	0.822**#	0.91	0.18	0.10
Hong Kong	0.605**#	0.81	0.40	0.25
Korea	0.837**#	0.96	0.16	0.13
Singapore	0.364**##	0.86	0.64	0.58
China	0.251*##	0.70	0.75	0.64
Malaysia	0.334**##	0.60	0.67	0.44
Thailand	0.271**##	0.59	0.73	0.54
Philippines	0.109##	0.82	0.89	0.87
Indonesia	0.366*##	1.02	0.63	0.64

Note: The degree of specialization= $\hat{\beta}$ / $\hat{R}$, the regression effect = (1- $\hat{\beta}$), and the mobility effect = (1-$\hat{R}$).
** denotes significantly different from zero at the 1% level.
* denotes significantly different from zero at the 5% level.
denotes significantly different from unity at the 1% level.
# denotes significantly different from unity at the 5% level.

According to the analyses above, Japan and Hong Kong already showed cumulative and incremental specialization patterns (β -de-specialization) since the period 1963 - 74, and it can be seen that Taiwan and Indonesia entered cumulative and incremental specialization patterns from the period 1975 - 84, while South Korea, Singapore, China, Malaysia and Thailand entered from the period 1985 - 94 (prior to which they had random specialization patterns). Japan maintained a path-dependent specialization pattern under which the RSTA distributions and variances did not change over the two periods, since 1975 - 84. In Singapore the specialization patterns for the two periods of 1975 - 84 and 1995 - 2005 were reversed, but from 1985 - 94 it moved into cumulative and incremental specialization pattern. Finally, only the Philippines still maintains a random pattern. These facts make clear the following. Firstly, for the period analyzed, in East Asia there were no cases of $\beta > 1$, which would indicate that a cumulative pattern was enhanced (β -specialization). Secondly, many of the countries had a predominantly random pattern from the 1960s to the first half of the 1980s during which the numbers of patents were small. Thirdly, since the mid-1980s, many countries experienced an increase in numbers of patents and simultaneously moved into cumulative and incremental specialization pattern (β -de-specialization). This accords with Cantwell's (1989) conclusion that 'the statistical evidence on international sectoral patterns of technological advantage offers support to the idea that innovation tends to unfold as a cumulative process, accompanied by gradual incremental change'.

Regarding the change in the degree of technological specialization, for the periods 1963 - 74 and 1995 - 2005, only Taiwan and Indonesia were increasing (σ -specialization or narrow specialization), and the other 8 countries were decreasing (σ -de-specialization or broad specialization). Since then, the degree of specialization increased in only Indonesia and Japan (although Japan was mostly homoscedastic), and the opposite, σ-de-specialization, was demonstrated by the other 8 countries. According to Cantwell's (1991) analysis which used the RTA with respect to the OECD countries with 27 sectors, an increase in the degree of technological specialization over the periods 1963 - 69 and 1977 - 83 was seen in 11 of 19 countries. According to the analysis by Archibugi and Pianta (1994) of the OECD countries using the RTA with 41 sectors, an increase in the degree of specialization was seen over the periods 1975 - 81 and 1982 - 88 for 11 of 16 countries. On the other hand, under the analysis of the OECD countries using the RSTA with 19 sectors by Laursen (2000), an increase in the degree of specialization over two sub-periods (1971 - 73 and 1980 - 82, together with 1980 - 82 and 1989 - 91) was seen in, respectively, 11 and 10 of 19 countries, but over the whole period (1971 - 73 and 1989 - 91) an increase in the degree of specialization occurred in only 6 of the 19 countries[11]. It can be seen from the analyses of the developed countries that the degree of technological specialization increased in many of these countries. In contrast, the research presented in this paper reveals a decreasing degree of specialization for most countries. Regarding this point, the results indicate that the number of patents from what was originally a small number has expanded from a narrow to a broader range of sectors in the periods analyzed. This can also be seen from the fact that the average annual growth rate in the number of U.S. patents granted for the East Asian region, excluding Japan, greatly exceeded that of the developed countries. This occurred together with a cumulative and incremental technological specialization pattern, that is, a combination of β-de-specialization and σ-de-specialization. However, in the final analysis period while many of the countries experienced σ-de-specialization, an increase in $\hat{\beta} / \hat{R}$ suggested that the degree of technological specialization in East Asia may increase in the future (towards σ-specialization) in accordance with the theory of technological accumulation.

4. Concluding Remarks

This paper statistically investigated three propositions regarding the pattern of technological specialization for 10 countries in East Asia using patent data. The results obtained from this research are as follows.

(1) The technological specialization patterns among the East Asian economies reflect the technological accumulation to date and many of the countries have different patterns. In particular, there is a large divergence between the specialization pattern of Japan and those of the other countries, suggesting that a complementary specialization pattern exists between them. A trend was also observed according to which small countries and those with a low level of development had a high degree of specialization.

(2) By the latest periods (1985 - 94 and 1995 - 2005) at least 8 of the 10 countries in East Asia had moved from a random technological specialization pattern to a cumulative and incremental pattern reflecting technological accumulation. On the other hand, since 1975 - 84 Japan moved from its previous cumulative and incremental pattern to a cumulative and path-dependent technological specialization pattern. Only the Philippines maintained a random technological specialization pattern for all the periods.

(3) Regarding the change in degree of technological specialization, most of the countries exhibited specialization over a broad range (σ-de-specialization) in parallel with an increase in the number of U.S. patents. Also, based on the fact that the regression effect exceeded the

mobility effect for many of the countries, the decrease in the degree of technological specialization was achieved in parallel with a stable pattern of specialization sectors. In the case of Japan, the degree of technological specialization remained mostly unchanged, reflecting a path-dependent technological specialization pattern.

The degree of technological specialization decreased for many of the countries in East Asia, but this reflects the fact that the increase in the number of U.S. patents granted for the East Asian region has extended over a broad range of sectors. On the other hand, according to Cantwell (1991), and Archibugi and Pianta (1992), the degree of specialization increased for the developed countries of Europe and the U.S. This is thought to reflect the differences in technological accumulation pattern between developed and developing countries, that is, the parallel economic development and expansion in technological accumulation initially caused an increase in the number of patents over a broad range of sectors, but there is a possibility that the number of patents in the specialized sectors subsequently increased in comparison. Alternatively, it is possible that the RSTA index used in this research led to differences with respect to the estimation results of Cantwell (1991), and Archibugi and Pianta (1992) who used the RTA index. In fact, the analysis of OECD countries by Laursen (2000) using the RSTA index obtained similar results to this research. Furthermore, while the degree of technological specialization decreased according to this research, the fact that the value of $\hat{\beta}/\hat{R}$ itself had a gradually increasing tendency for many countries means that from this point it will surely be important to establish whether or not $\hat{\beta}/\hat{R}>1$ will occur in the future, as suggested by the theory of technological accumulation.

notation

1 An alternative proposition on the other hand, is that technological changes follow a random course, and since the sectors of specialization periodically switch, specialization patterns are unstable.

2 According to the World Economic Forum (2005), in an analysis involving 117 countries, there were a total of 25 countries constituting core technology-innovating economies focused on innovation (economies with at least 15 US patents per million population in 2004), and in East Asia, besides Japan (ranked 2nd), the ranked countries included Taiwan (3rd), Singapore (10th), South Korea (11th), and Hong Kong (23rd). The East Asian region also fared well with respect to the technology index which functions as a comprehensive index of technological capability, with Taiwan (ranked 3rd), South Korea (7th), Japan (8th), Singapore (10th), Malaysia (25th) and Hong Kong (26th). From the perspective of the average annual growth rate in numbers of U.S. patents through 2000 to 2005, while the world, Japan and the U.S. had negative growth rates of -1.8%, -0.62% and -2.58%, respectively, there was momentum in China 27.6%, ASEAN4 (Thailand, Malaysia, Indonesia and the Philippines) 15.2%, Singapore 9.7%, Hong Kong 9.6%, South Korea 5.6% and Taiwan 1.9%.

3 The advantages and disadvantages of patent data as an indicator of technological activity are now well documented (for a review of the literature see Pavitt 1985, Archibugi and Pianta 1992). While it is true that some innovations are never patented, and that some patents either have little qualitative impact or are never used, this leads principally to systematic industry-specific and country-specific differences, as it seems that firms from the same sector in any country have a similar propensity to patent (Sherer, 1983, Cantwell, 1989). Once inter-industry differences are accounted for, patenting as a measure of innovative output is strongly correlated with a widely used measure of innovative input (as measured by R&D expenditure).

4 In this study, we do not use the NBER database since the main data set is restricted to the period from January 1, 1963 through December 30, 1999. The details of the database of U.S. patents are described in Hall, Jaffe and Tranjtenberg (2001).

5 The problems of patents as an indicator of technological specialization are even more significant for developing countries because their total number of patents is small during the early stages of industrialization. It is therefore necessary that each period used for analysis is large enough to ensure a certain volume of patents.

6 In particular, the increase in the number of patents in East Asia occurred from the 1990s, so before this period there were sectors with zero patents for a number of countries. Logarithmic transformation has often been used as a means for dealing with small numbers of samples (Soete and Verspagen, 1994), but this method has the problem that when there are sectors with zero patents, the value after logarithmic conversion is also zero.

7 $\sum_j \varpi_j RTA_{ij} = 1; \varpi_j = \left(\sum_i n_{ij} \Big/ \sum_i \sum_j n_{ij}\right)$

8 To put it precisely, if there is a path-dependent cumulative process with no change in the technological association between sectors, and if this causes a lack of any further shift in the structure of industrial innovation (there is no incremental change), the ratio of each industry's innovation advances towards a stable and fixed position. This corresponds to the case that $\hat{\beta} = 1$, and the regression effect $(1 - \hat{\beta}) = 0$ described below. Also, in the case that $0 < \hat{\beta} < 1$, the two factors of cumulative and incremental change are combined. Thus, in the case that accumulation exceeds incremental change, $\hat{\beta} \geqq 1$ (which is equivalent to the regression effect being negative or zero).

9 China, Thailand and Philippines also have $\hat{\beta} / \hat{R} < 1$ and the regression effect exceeds the mobility effect like Taiwan and Hong Kong, but we have not refer to them because their $H_0 : \beta = 0$ cannot be rejected .

10 In addition, Laursen (2000) confirmed that only in France and the U.S. are the $|\hat{\beta} / \hat{R}|$ significantly different from one (i.e., the hypothesis of equal variances, across the two periods, can be rejected in a few cases). It was thus concluded that 'while σ de-specialization is not a strong trend, we are certainly not experiencing σ-specialization'.

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References

[1] Andersen, B., 2001. Technological Change and the Evolution of Corporate Innovation. The Structure of Patenting 1890-1990, Cheltenham: Edward Elgar.

[2] Andersen, B. and Howells, J., 2000. Intellectual property rights shaping innovation dynamics in services, In Andersen, B. et al (eds.) Knowledge and Innovation in the New Service Economy, Cheltenham: Edward Elgar.

[3] Archibugi, D. and Pianta, M., 1992. The Technological Specialization of Advanced Countries. A Report to the EEC on International Science and Technology Activities. Kluwer, Dordrecht

[4] Archibugi, D. and Pianta, M., 1994. Aggregate convergence and sectoral specialization in innovation, Journal of Evolutionary Economics 4: 17-33.

[5] Arthur, W.B., 1988. Competing technologies: an overview, in Dosi, G., Freeman, C. Nelson, R. Silverberg, G. and Soete, L. (eds.) Technical Change and Economic Theory, London: Frances Pinter.

[6] Balassa, B., 1965. Trade liberalization and 'revealed' comparative advantage, The Manchester School of Economics and Social Studies 32(2): 99-123.

[7] Barro, R. J. and Sala-i-Martin, X., 1991. Convergence across states and regions, Brooking Papers on Economic Activity, pp. 107-182.

[8] Bell, M. and Pavitt, K., 1997. Technological accumulation and industrial growth: contrasts between developed and developing countries, in D. Archibugi and J. Michie (eds.) Technology, Globalization and Economic Performance. Cambridge University Press

[9] Cantwell, J., 1989. Technological Innovation and Multinational Corporations. Oxford: Blackwell.

[10] Cantwell, J., 1991. Historical trends in international patterns of technological innovation, In Foreman-Peck, J. (ed.) New Perspectives on the Late Victorian Economy. Cambridge: Cambridge University Press.

[11] Choung, J.-Y., 1998. Patterns of innovation in Korea and Taiwan, IEEE Transactions on Engineering Management 45(4): 357-365.

[12] Dalum, B., K. Laursen and G. Villumsen, 1998. Structural change in OECD export specializations: de-specialization and 'stickiness', International Review of Applied Economics, Vol. 12, No. 3, 423-443.

[13] Hall, B.H., Jaff, A.B. and Tranjtenberg, M., 2001. The NBER patent citations data file: lessons, insights and methodological tools, NBER Working Paper 8498.

[14] Hart, P. E. and Prais, S.J., 1956. The analysis of business concentration: a statistical approach, Journal of the Royal Statistical Society (series 2) 119 (2) : 150-91.

[15] Hart, P. E., 1976. The dynamics of earnings, 1963-1973, Economic Journal, 86, 551-565.

[16] Henderson, R.M. and Clark, K.B., 1990. Architectural innovation: the reconfiguration of existing product technologies and the failure of established firms, Administrative Science Quarterly 35: 9-30.

[17] Huang, H.-T. and Miozzo, M., 2004. Patterns of technological specialization in Latin American and East Asian countries: an analysis of patents and trade flows, Economics of Innovation and New Technology 13(7): 615-653.

[18] Laursen, K., 2000. Do export and technological specialization patterns co-evolve in terms of convergence or divergence? Evidence from 19 OECD countries, 1971-1991, Journal of Evolutionary Economics 10: 415-436.

[19] Mahmood, I. P. and Singh, J., 2003. Technological dynamism in Asia, Research Policy 32: 1031-1054.

[20] Miyagi, K., 2006. Empirical study on the patterns of technological specialization and innovation: a comparative analysis of Taiwan and Korea, The journal of Science Policy and Research Management 21(1): 105-116

[21] Patel, P. and Pavitt, K., 1994. Uneven (and divergent) technological accumulation among advanced countries: evidence and a framework of explanation, Industrial and Corporate Change 3(3): 759-787.

[22] Pavitt, K., 1985. Patent statistics as indicators of innovative activities: possibilities and problems, Scientometrics 7 (1 − 2) : 77-99.

[23] Pavitt, K., 1988. International patterns of technological accumulation, in Hood, N. and Vahne, J.E. (eds.) Strategies in Global Competition, London: Croom Helm.

[24] Rosenberg, N., 1982. Inside the Black Box: Technology and Economics, Cambridge: Cambridge University Press.

[25] Scherer, F.M., 1983. The propensity to patent. International Journal of Industrial Organization 1, 107-128.

[26] Soete, L., 1987. The impact of technological innovation on international trade patterns: the evidence reconsidered. Research Policy 16: 101-130.

[27] Soete, L. and Verspagen, B., 1994. Competing for growth: the dynamics of technology gaps. In Pasinetti, L.L. and Solow, R.M. (eds.) Economic Growth and the Structure of Long-Term Development. London: Macmillan.

[28] Soete, L. and Wayatt, S., 1983. The use of foreign patenting as an internationally comparable science and technology output indicators. Scientometrics 15(2): 31-54.

[29] Tsuhman, M.L. and Anderson, P., 1986. Technological discontinuities and organizational environments, Administrative Science Quarterly 31: 439-465.

[30] World Economic Forum, 2005. The Global Competitiveness Report 2005-2006. Policies Underpinning Rising Prosperity, Palgrave Macmillan