The Determinants Of Technological Specialization and Its Dynamics

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May, 2001

Preliminary Draft

We are grateful to Andrea Porcu, Maurizio Regali, Giorgio Rivero e Francesco Rampa for valuable research assistance. Citations data were provided to us by Bart Verspagen. The usual disclaimer applies. This paper is part of the Research Project: Sectoral Systems in Europe - Innovation, Competitiveness and Growth (ESSY). Third Research and Technological Framework Programme, Targeted Socio-Economic Research, TSER [Contract no: SOE1-CT 98-1116 (DG 12-SOLS)]. Short-term mobility program by Italian CNR is also gratefully acknowledged (Prot. 031883).

0. Introduction

Analysts have studied technological specialization of countries focusing mainly on three sets of issues: convergence between countries in the degree of technological specialization, its persistence or stability over time and, finally, the comparison across countries of patterns of technological specialization and their relative dynamics.

Our paper aims at advancing the analysis studying at a very fine level of dis-aggregation the nature of the dynamics of international technological specialization of countries. We consider the processes of knowledge accumulation, embedded in cumulative research activities, in the development of domestic knowledge linkages between technological classes, in the innovative activities by universities and public research institutes, and, finally, in the activity of technological co-operation between innovative firms. Moreover we enquiry about the impact of different sectoral structures of innovative activities in terms of concentration and frequency of new entrants. In particular we perform an econometric analysis, which studies the relationship between these variables and patterns of technological specialization, assessing differences across sectors in the relevance of the factors affecting international specialization.

1. Literature Review

A growing body of empirical research has focused on a set of open issues about patterns of countries' technological activities and specialization. Firstly there is no clear cut evidence about convergence of the level of countries technological activity. Countries converge in terms of total R&D and diverge in terms of R&D performed and financed in industries. At the same time evidence suggests that industrialized countries converge in terms of patent applications abroad per unit of export and diverge in terms of per capita patenting (Archibugi, Pianta, 1994; Patel, Pavitt, 1994).

Secondly the empirical literature has focused on the patterns of technological specialization and its dynamics. Evidence is here based on various specialization indexes built upon patent grants and applications in US and EU. First evidence provided by Cantwell (1991), Patel, Pavitt (1994) and Archibugi e Pianta (1992, 1994) shows that countries get more specialized and become increasingly less similar in their technological profile. Large countries, though, are less specialized and display a higher degree of persistency. At the same time Laursen (2000) finds mixed evidence and therefore less conclusive results on technological specialization and Laursen (2000) and Mancusi (2000) find that, independently of country size, there is a significantly high degree of mobility across technological classes. As a result even if specialization patterns are not random and significantly persistent, constraints on technological trajectories becomes less binding over time.

Three different types of explanation have usually been put forward to account for the persistence of patterns of technological specialization and their cross-country variance. First, the location specific advantages for innovation activities, due to specific characteristics of the national (or regional) institutional and economic environments, have been stressed. These considerations led to the construction of the concept of national systems of innovation (Lundvall, 1992, Nelson, 1993, Edquist, 1997, Montobbio, 2000) and, more recently, of regional systems of innovation (Cooke, 1997; Howells, 1999). The innovative activity of multinational corporations is also expected to increase country specialization as long as it is increasingly performed in the regions where positive externalities and increasing returns can be more easily grasped (Patel and Pavitt, 1994; Cantwell, 1995; Patel, 1995).

A second tradition focuses more on firm organization and on learning (Nelson, Winter, 1982; Teece, 1988; Malerba, 1992; Dosi, 1988, 1997). According to these authors, technological advancements include, first, improvements on a specific set of industrial methods and systems of production and, secondly, knowledge accumulation, which does not depend only on freely available and codified blueprints, manuals and operating instructions, neither on exogenous science. Rather technological knowledge is to a great extent built on previous experience and on learning processes about un-codified and tacit understanding and competence. As a result the technological opportunity frontier is limited and guided by the specific procedures that agents build within a specific set of institutional interactions.

Finally, a third strand focuses on the characteristics of market structures and the patterns of innovative activity (Pavitt, 1984; Dosi, 1988; Malerba, Orsenigo, 1996). If sectors are characterized by relatively invariant modes of search for novelty and innovation, if this implies different typology of innovative firms according to a set of specific technological imperatives, we can expect that technological specialization is associated with a specific profile in terms of firms characteristic, concentration of innovative activities and degree of technological entry. Evidence provided by Malerba and Orsenigo (1997) and by Malerba et al. (1996) suggests a positive association between technological specialization and concentration in the innovative activity and, therefore, with a competitive core of persistent innovators.

2. Knowledge accumulation, market structures and technological specialization

Surprisingly less attention has been paid to the analysis of the determinants of the international technological specialization of countries. In particular while considerable effort has been placed on searching for regularities in patterns of specialization and its evolution, there is scarce evidence on the determinants of technological specialization and its dynamics, which is consistently comparable across countries and sectors. We move in this direction addressing three related sets of issues. In sections 3 and 4 we use two different specifications to investigate the role of a set of explanatory variables in the following reduced form:

$$RTAN_{ijt} = f(RTAN_{i,j,t-1}, A_{i,j,t}, MS_{i,j,t}, PO_{i,j,t})$$

The reduced form relates the specialization of country i in technological class j at time t to a series of explanatory variables. In order to assess technological specialization we use the normalized technological specialization indexes: $RTAN_{ij}$. This index is the transformed index of revealed technological advantage[1] (Balassa, 1965).

[1] The index of revealed technological advantage is defined as:

$$RTA_{ij} = \frac{p_{ij}}{\sum_i p_{ij}} \Bigg/ \frac{\sum_j p_{ij}}{\sum_i \sum_j p_{ij}}$$

and then standardized in the following way:

Knowledge accumulation, domestic knowledge linkages across sectors and institutions (A_{ijt}).

It has been widely recognized that countries technological dynamics depends on the ability of a country to create, accumulate and absorb knowledge. Technological accumulation is not a random process and is not a simple by-product of production and economic activities. Deliberate investment in research by private firms, public institutions and universities, the quality of this research and the ability to transfer and absorb novelty have importantly affected countries technological development (Bell, Pavitt, 1993; Nelson, 1992, 1993). The same determinants have also influenced trade and economic performance, as shown by the technological gap tradition (Soete, 1981; Dosi et al., 1992; Amable Verspagen, 1995; Magnier Toujas Bernate, 1994; Montobbio, 1999).

In this paper we assume that the process linking knowledge creation and accumulation to technological specialization is guided by four factors. First we consider past and present *investment in research and development* performed by firms and funded both within industries and by public organizations. Moreover we assume that technological specialization is affected by the accumulation of knowledge capital stock in specific technological classes. This is built through a continuous and persistent flow of R&D spending and is also subject to a knowledge depreciation rate as new products and processes develop. Moreover R&D is also expected to increase the ability of firms to learn and to absorb information developed outside the boundaries of the firm improving further firms' innovation potential (Cohen, Levinthal, 1989).

Secondly knowledge arises from research performed by public institutes and universities. In particular we believe that the *quality of the research output by public institution and universities*, which is to some extent non rival and non excludable within a country, is an important factor in guiding and enhancing technological specialization. This is particularly true when public research has tangible outcomes in developing the knowledge bases in specific core technologies (Nelson, 1993).

Thirdly technological accumulation depends upon the ability by firms of integrating and using high quality knowledge coming from different sources and different technological classes. Therefore strong intersectoral linkages are expected to affect importantly the direction of technological specialization. In this paper we test the hypothesis that international technological specialization of a country in a specific technology is positively affected by strong *local knowledge links* with those technologies in which the country is internationally specialized. Through knowledge links, a country will be able to benefit from its specialization in other technologies which are knowledge related.

Finally we consider knowledge accumulation coming from the co-operation activities of firms within countries. We enquiry whether a greater amount of *technological co-operation* is conducive to greater technological specialization at the country level because it increases the diffusion of knowledge, it gives access to complementarities and it reduces the amount of uncertainty that each firm is facing in innovative activities.

$$RTAN_{ij} = \frac{(RTA_{ij} - 1)}{(RTA_{ij} + 1)}$$

p_{ij} is the total amount of patent applications in the technological class j by country i. RTAN is a monotonic transformation of RTA which better is suited to describe technological specialization because is symmetric and reduces the value of extreme observations. It has values which belong to the [–1,1) set. $RTAN_{ij}>0$ ($RTAN_{ij}<0$) means that country i is relatively specialized (de-specialized) in class j. The same applies for RCAN which is built on export data. In our data set the extreme values are -1 and 0.643 for RCAN and –1 and 0.87 for RTAN.

Sectoral profit and technological opportunities (PO_{ijt}).

A considerable amount of literature has recently shown that purposeful innovation activity is performed in response to economic incentives (Grossman, Helpman, 1991). As a result we expect technological specialization to be determined not only on the basis of technological and scientific advancements, but also driven by profit opportunities and market expansion. In this respect particular attention has been recently paid to the analysis of the relationship at firm level between export activities and rates of innovation (Aw et al., 2000; World Bank, 1993). Export has often been seen as an important channel of technological transfer from buyer to seller, which also originates knowledge spillovers to the whole economy. As a result we expect that high levels of export and trade specialization in specific technological classes may signal profit opportunities, foster best practice techniques and learning and, in turn, affect technological specialization.

Market structures (MS_{ijt})

A classical schumpeterian theme in industrial organization is the relationship between firm size, market structures and innovation activities. Many authors agree that technological accumulation is a process largely driven by large firms (Cantwell, 1989; Patel, Pavitt, 1994, 1995; Nelson, 1993). Evidence shows that big multinational companies do not smooth international differences in technological specialization and, rather, they tend to concentrate their technological activity in the home market and concentrate geographically. At the same time, according to the technological characteristics of sectors, technological development depends upon the emergence of new, often small, firms, bringing into the market new skills and technological capabilities. This seems to be the case in components and industry suppliers and in those sectors characterized by high turbulence (like machine tools, mechanical engineering and clothing and shoes) (Malerba, Orsenigo, 1995; Breschi et al., 2000).

This raises the question whether the cross-country variance in technological specialization can be associated to different country features of the structure of innovation activity, under the assumption that specific structural archetypes are better suited to respond to specific technological imperatives. This would imply an association between technological specialization and specific features of firm level structures of innovation activities. As a result, in this paper we test, first, whether countries' international specialization is positively affected by a higher degree of innovative concentration in a technological class. Countries are, then, expected to be more specialized in the technological classes with a strong oligopolistic core of innovators.

Secondly we ask whether countries could benefit from some degree of technological entry. New entrants in fact bring in new ideas, new technologies and new products. Thus some turbulence would be beneficial to countries even in highly concentrated sectors. In each sector, then, core and fringe innovators can coexist. While the relative balance between the two differs across sectors, on average the presence of a stable oligopolistic core and of a fringe of dynamic innovative entrants favors innovation and international specialization.

Finally since previous empirical research has shown the existence of specific patterns of innovative activity in terms of concentration and entry (Breschi et al., 2000), it is also worthwhile enquiring whether specific combinations of the two structural variables can be associated with specific features of technological specialization.

Persistence of patterns of technological specialization ($RTAN_{i,j,t-1}$)

All the relations above have to be controlled for the persistency of country technological specialization observed by many authors. In particular we will test whether our explanatory variable are statistically significant against the null hypothesis that revealed technological advantages simply depend upon their values in the previous period.

Differences across sectors

Starting from the claim that there are differences across sectors in knowledge, patterns of innovative and production activities, and linkages, we test whether the role of the variables discussed above differs among three major sectoral systems: electronics, chemicals and machinery. Although these broad sectoral systems are composed by a large set of different micro sectors and technologies (which we capture in our disaggregated analysis), major differences exist among them in the knowledge, technologies and scientific fields that are at the base of firms innovative and production activities. As a consequence differences in the basic knowledge, technologies and scientific fields are expected to affect the processes linking knowledge accumulation, inter-sectoral-linkages, Schumpeterian variables, technological cooperation and countries' technological specialization profiles.

2.1 The Data: Patents Applications and Citations, Research and Development and International Trade.

The data set is composed by patent applications (EPO/CESPRI), patent citations[2], export values (OECD, ITC) and Business Enterprise R&D (OECD, ANBERD, 1999). Six countries are considered: United States, United Kingdom, Japan, Italy, France, Germany. In section 3, the period covered is from 1989 to 1994 and the values are averages on three sub-periods, 1989-1990, 1991-1992 and 1993-1994[3]. We consider 135 technological classes in three industrial sectors, in particular we have 58 chemical technological classes, 38 electronic technological classes and 36 machinery technological classes[4]. The technological classes are listed in Tab. A.2 in the Appendix. The concordance between IPC classification and SITC classification is provided by Grupp, Munt, (1995). The concordance between our technological classes and the R&D ISIC classification has been developed by the authors and is presented in the Appendix.

[2] CESPRI/EPO data-set has 919451 patent applications for the period 78-96. Firms that are part of business groups have been treated as individual companies. In case of co-patenting each co-patentee has been credited the patent. In the period 89-94 in Germany, France, Italy and US, CESPRI/EPO has 225987 patent applications. Our 135 classes covers 152913 patent applications (68% of EPO). The total number of patent applications for each technological class, for the 89-94 period for the four countries, ranges from 105 (Organic oils and fat) to 7731 (Computers and equipment). This is because we have excluded from the analysis technological classes with a total number of patents in all countries is lower than one hundred (accordingly in the empirical work we used only 111, out of 135, technological classes). The average number of patent applications per technological class is 1368. The median is 973. Citations are considered for the whole period (78-96). The total amount of citations is 799038. The citations between our 135 classes are 437752.

[3] This choice is due to export data availability with SITC Rev. 3 sectoral classification, which is used in the FHG_ISI concordance table with IPC (Grupp, Munt, 1995).

[4] In what follows we use 'technological class' to refer to the lowest level of disaggregation (135 classes). We call 'sectors' the three groups of technological classes: Chemicals, Electronics and Mechanics (See Tab. A.2 in the Appendix).

3. Technological Specialization, Knowledge Links and the Structure of Innovative Activity[5]

3.1 Knowledge Flows: Citations

Citations[6] are used to track the flows of knowledge between classes and to assess the quality of the cited patents and, therefore, of the patterns of specialization. We have built a square asymmetric citation matrix CIT for each country. Each element of the matrix $\{CIT^k_{ij}\}$ represents the amount of patent citations flowing from technology j (in country i) into technology k (in country i). The amount of citations which 'stays' in the same technological class in a specific country i is caught by the elements on the main diagonal $\{CIT^j_{ij}\}$. If we define CIT_{ij} the total amount of citation flowing out technological class j of country i (the sum of the j-th row of the matrix) then

$$CIT_{NODIAGij} = \sum_{k \neq j} CIT^k{}_{ij} = \sum_k CIT^k{}_{ij} - CIT^j{}_{ij} = CIT_{ij} - CIT^j{}_{ij}$$

is the number of citations flowing out from class j with the exclusion of citations within the same technological class.

Note that the sum of the elements of the main diagonal of CIT, divided by the overall amount of citations in each country, range from 0.74 in US to 0.79 in Italy. As a result more than three quarters of the total amount of citations in each country flows within the same technological class. These values are higher for the machinery sector (on average 0.86) and relatively lower in the chemical sector (on average 0.72).

3.2 The Variables and the Econometric Specification

First, we inquire whether knowledge links are important for technological specialization in all countries and technologies. In particular we ask whether technological specialization is related to specialization in the cited classes. We expect countries to have a higher specialization in a specific technological class j if, in parallel, they display a higher specialization in the cited class *relatively* to other countries. This brings about two consequences: first we have to build an index which has to jointly account for the relative amount of citations towards a specific technological class and for the countries relative specialization in the cited classes. Second our econometric specification is bound to be cross-country. The proposed index is the following:

$$\mathrm{LINKCIT}_{ij} = \sum_{k \neq j} \mathrm{u}^k{}_{ij} \mathrm{RTAN}_{ikt}$$

k,j=1,...., 111. Technological classes,
i=1,..., 6. Countries,

where $u^k_{ij} = CIT^k_{ij} / CIT_{NODIAGij}$.

$LINKCIT_{ij}$ values belong to the (-1, +1) interval. Positive values (for country i and technological class j) point to the existence of strong knowledge linkages in terms of citations with sectors in which country i tends to

[5] Section 3 heavily draws upon Malerba, Montobbio (2001).

be specialized. Negative values emphasize that technological class j in country i is connected, in country i, with sectors with technological revealed disadvantages. As a result we expect a positive relationship between $LINKCIT_{ij}$ and $RTAN_{ij}$. The elements on the main diagonal of the matrix CIT (for each country i) have been excluded in the computation of the index. This is because we point at the knowledge connections of class j with technological classes different from j.

According to our hypotheses on market structure (Section 2), we include in the econometric specification two Schumpeterian variables indicating the structure of the innovative activity. They are:

$HERF_{ij}$: the Herfindahl index in class j, country i.

$ENTRY_{ij}$: the share of firms, which innovate for the first time, in class j and country i.

$HERF_{ij}$ and $ENTRY_{ij}$ are built in order to assess the effects of innovative concentration and entry on technological specialization. We expect a positive effect of $HERF_{ij}$ and $ENTRY_{ij}$, on $RTAN_{ij}$ because technological advantages of countries could benefit from the presence of both a core of stable and persistent innovators and from the presence of a pool of new innovators exploiting new technological opportunities.

Finally the technological co-operation variable is: $COPATF_{ij}$. It is the amount of co-patenting firms in class j and country i divided by the total number of patenting firms in class j. $COPATF_{ij}$ represents the propensity to co-patent of firms in a specific technological class and country. It ranges between 0 and 1. This proxy clearly covers a small part of the possible collaborations between firms' innovative activities. Nevertheless we believe that it is worthwhile to ask whether even the association of this small aspect of technological co-operation with international technological specialization is statistically significant.

Our benchmark specification is:

$$RTAN_{ij} = \alpha + \tau_s RTAN(-1)_{ij} + \beta_s LINKCIT_{ij} + \phi_s COPATF_{ij} + \eta_s ENTRY_{ij} + \lambda_s HERF_{ij} + \varepsilon_{ij} \qquad (1)$$

j=1,...., 111. Technological classes,
i=1,..., 6. Countries,
s=1, ,3 Sectors.

3.3 The Results

We estimate Equation 1 in a cross-section framework using the pooled sample for the sub period 93-94 (Tab. 1). Our specification is tested against two hypotheses:

- that revealed technological advantages are randomly distributed across countries and sectors (see X^2_{TOT} in Tab. 1),

[6] Citations data have been kindly provided to us by Bart Verspagen. The idea that patent citations are a valuable indicator of both the importance of the technology as well as the extent of knowledge spillovers is strongly supported by Jaffe et al. (2000).

- that revealed technological advantages simply depend upon their values in the previous period (see X^2_lag1 in Tab. 1).

POLS estimation displays for sector-wise heteroscedasticity (Chemicals, Electronics and Mechanics)[7]. Feasible generalized least squares are then used to estimate the coefficients. Moreover differences across countries and sectors are tested with country and sector fixed effects but the F tests effects accept the restriction of equality of the intercept term. We control also for collinearity among the explanatory variables. Correlation matrices (Tab A.1 in the Appendix) show that there is no severe collinearity between independent variables. Finally, as we argued in Section 2, the existence of macro-sectoral specific knowledge features suggests that the relationships between the knowledge, schumpeterian and technological collaboration variables and the patterns of technological specialization of countries can be sector specific. In this framework we can assess sectoral diversity from three points of view: coefficients' significance and magnitude in different sectors and non-linearities. Accordingly sectoral specificity is accounted for in the estimated values of the slope coefficients and the appropriate test rejects the hypothesis of their sectoral homogeneity (see X_{SLOPE} in Tab. 1).

Tab. 1 shows that, consistently with our expectations, technological specialization is positively associated with our knowledge variable. The high positive value of the estimated coefficients of intensity of knowledge linkages with other technological classes in which countries have advantages ($LINKCIT_{ij}$) is particularly noteworthy. This also implies the negative effect of strong knowledge linkages with unspecialized technological classes. The positive signs indicate that higher knowledge connections (in terms of citations) with technological classes with high specialization are associated with higher technological advantages in the citing class. With regard to the Schumpeterian variables, we observe that technological advantages are positively associated with the index of innovative concentration ($HERF_{ij}$). $RTAN_{ij}$ are also positively correlated with $ENTRY_{ij}$ (in two sectors out of three). The significantly positive relation between $ENTRY_{ij}$ and technological specialization suggests that the existence of a pool of new innovators exploiting latent technological opportunities may be very important for the generation of technological advantages.

The estimated relationship between concentration and technological advantages might not be independent from the rate of entry of innovative firms. In particular it is plausible that technological specialization is affected by a specific combination of concentration and rates of entry. Therefore we added an interaction term ($ENTRY_{ij}$*$HERF_{ij}$) between concentration and entry which tests whether the marginal effect of higher innovative concentration on technological advantages is decreased when entry is higher. The estimated interaction term coefficient does not reject the hypothesis that technological specialization is affected by a specific combination of concentration and rates of entry in two sectors out of three. In particular, since for these two sectors $ENTRY_{ij}$*$HERF_{ij}$ is significantly negative, we can claim that the positive relation between the Herfindahl index and $RTAN_{ij}$ is lower in presence of entrants competing with incumbent firms and, alternatively, that the positive relationship between the $ENTRY_{ij}$ and $RTAN_{ij}$ turns out to be lower in presence of higher concentration.

[7] The Cook-Weisberg test: ^{2}=8,17** returns evidence of sector-wise heteroscedasticity. Conversely there is no evidence of country wise heteroscedasticity (Cook-Weisberg test: ^{2}=0,17)

Finally we tested for non linearity in the relation between the Schumpeterian variables and $RTAN_{ij}$ also including the squared terms for $ENTRY_{ij}$ and $HERF_{ij}$. The squared term of $ENTRY_{ij}$ is significantly different from zero only in one sector, while the squared term for $HERF_{ij}$ is never significantly different from zero and therefore is dropped from the regression.

The level of technological co-operation among firms, as expressed by the share of co-patenting firms on the total amount of patenting firms ($COPATF_{ij}$), is positively associated with technological specialization in two sectors out of three. Even if this index catches only a very limited portion of the many possible forms of firms collaboration, our evidence suggests that it has a positive impact on the construction of technological advantages.

Finally, the relevance of sectoral differences has been tested on the knowledge variable $LINKCIT_{ij}$, whose estimated value is particularly high in the Chemicals and Electronic sectors. Regarding the Schumpeterian variables, in the Machinery sector we observe a high value of the estimated effect of innovative concentration ($HERF_{ij}$) on $RTAN_{ij}$ and in the Electronic sector there is a strong estimated association of innovative entry ($ENTRY_{ij}$) on $RTAN_{ij}$. The interaction effect of $HERF_{ij}$ with $ENTRY_{ij}$ is significantly different form zero in Chemicals and Mechanics suggesting that in these technological classes concentration affects positively technological advantages only if it is not associated with a high share of new innovative firms. The same result, in a weaker form, holds for the technological classes in the Electronic sector. At the same time, just for the Electronic sector, results reported in Tab.1 show a non-linear relation between $ENTRY_{ij}$ and $RTAN_{ij}$ and, in particular, they suggest the existence of an inverted–U relationship. Both the linear and the squared terms for $ENTRY_{ij}$ are statistically significant and they presents opposite signs. We suggest, therefore, that in Electronics, technological specialization is most likely to be associated to higher level of entry, but only up to a certain threshold. In sum it turns out that the probability to observe that country i is specialized in a technological class j (in Electronics) is high for medium level of $ENTRY_{ij}$ jointly with small levels of innovative concentration ($HERF_{ij}$).

In sum specification 1 seems to catch important aspects of the relation between technological specialization and knowledge, structural and cooperation variables. It accounts for the 70% of the total RTAN variance and the hypothesis that RTAN is purely random across country and across technological classes is rejected (X^2_{TOT}=1239.31**). Moreover, as expected, the RTAN(-1) component is signficantly positive and confirms a well-known result on the past-dependency of specialization patterns. At the same time also the hypothesis that RTAN depends only on its one period lag value is rejected and the knowledge, Schumpeterian and cooperation variables can be jointly considered statistically significant (X^2_{TOT}=1239.31**).

4. Towards a dynamic specification

Specification (1) in section 3 can be improved in the direction of a full dynamic specification. Accordingly we expand the dataset and use yearly observations over the period 1981-1994. We extend the previous analysis introducing the following explanatory variables:

4.1 RD_{it}^{k}: *Research and development*

Investment in research and development performed by firms and funded both privately and by public organizations is assumed to affect the accumulation of knowledge capital stock in specific technological classes. In order to incorporate into a variable the continuous and persistent flow of R&D spending and a knowledge depreciation rate (Section 2), we have built an index based on cumulated R&D values (Gustavsson et al., 1999; Hall, Mairesse, 1995). Once we have built the stock of knowledge capital using cumulative constant price R&D, we have standardised it across countries and sectors in the usual form of normalized revealed research advantages (see footnote 1, Balassa, 1965): $RRAN_{ijt}$.

The stock of knowledge capital for technological class j, in country i, at time t, used to calculate $RRAN_{ijt}$, has been built in two ways. The related RRAN indexes have been called RRA5 and RRAS.

The first one is based on R&D expenditures cumulated over five years:

$$RD_{ijt} = \sum_{s=0}^{4} R_{i,j,t-s} \qquad (2)$$

$R_{i,j,t-s}$ = R&D expenditures in constant prices by country i, in sector j at time t-s.

The second measure follows Hall and Mairesse (1995) and is obtained from the stock of knowledge by industry and country:

$$S_{ijt} = (1 - d_S) S_{ijt-1} + R_{ijt-1} \qquad (3)$$

where d_S is the rate of depreciation of knowledge, i.e. the rate at which knowledge becomes obsolete. A benchmark S_1 is obtained as:

$$S_{ij1} = R_{ij1} / (g + d_S)$$

where g is the rate of growth of R&D (assumed constant over time)[8].

4.2 Quality of research output by the Public Research and Universities

Assume now that the stock of knowledge depends upon the quality of research output by the public research centers and Universities. We refer, then, to patents applied for by universities or public research centers. To assess quality we consider the average number of citations per patent in sector *j* and country *i* at time *t* in the 5 years following the application, normalized by the world average in the same technological class:

$$INTCIT_{ijt} = \frac{\dfrac{CIT^U_{ijt}}{P^U_{ijt}}}{\dfrac{CIT^U_{jt}}{P^U_{jt}}}$$

P^U_{ijt} is the number of patents at time t from universities and research centers in country i.

[8] Following Gustavsson et al. (1999), we use a depreciation rate of knowledge δ of 15%, a pre-sample growth in R&D expenditures g of 6% (cf. also Hall and Mairesse, 1995) and assume that investment in research add to the stock of productive knowledge capital with a lag of three years.

$CIT^{U}_{ijt} = \sum_{s=0}^{4} C^{U}_{i,j,t+s}$, where $C^{U}_{i,j,t+s}$ is the number of citations at time $t+s$ of patents applied for in sector j by universities and research centers in country i[9].

$CIT^{U}_{jt} = \sum_{k=0}^{6} CIT^{U}_{k,j,t}$ is the sum across countries of CIT^{u}_{ijt}.

$P^{U}_{jt} = \sum_{k=0}^{6} P^{U}_{k,j,t}$ is the sum across countries of P^{u}_{ijt}.

4.3 Sectoral profit and technological opportunities.

In order to account for that part of RTAN variance which is pulled for by technological incentives created by profit opportunities and market expansion, as argued in section 2, we consider relative advantages in terms of exports. In particular we have built the index RCAN in the form of normalized revealed comparative advantage (see footnote 1, Balassa, 1965).

In sum the second specification that we estimate is the following:

$$\begin{aligned} RTAN_{ijt} &= b_1 RTAN_{ij,t-1} + b_2 RRAN_{ijt} + b_3 INTCIT_{ijt} + \\ & b_4 HERF_{ijt} + b_5 ENTRY_{ijt} + b_6 RCAN_{ijt} + b_7 LINKCIT_{ijt} + e_{ijt} \end{aligned} \tag{4}$$

t=1, …, 14 years[10]

i = 1, …, 6 countries

j = 1, …, 100 technological classes[11]

In this dynamic specification, the technological specialization index and the structural variables (HERF and ENTRY) have been calculated as moving averages over a three-year period, each moving average being assigned to the central year. This has been done to smooth over the part of variance in yearly data originating in some institutional or random elements that we do not capture with our specification. In particular, with yearly data there can be an unpredictable element that creates jumps and discontinuities not explained by our model.

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[9] Since we have data on citations up to 1998, this is compatible with the time period we use for our regression which is from 1981 to 1994.

[10] The RCA index is available only over the period from 1988 to 1994.

[11] We eliminated from the analysis the technological classes with a low number of patent applications over the sample period to avoid the inclusion of too many zeros in the data (recall we employ yearly observations): all the technological classes with less than 500 patent applications over the whole sample period were excluded.

4.4 Results

Estimation of equation (4) entails several difficulties due to the panel structure and the inclusion of a lagged dependent variable among the regressors. Furthermore, we might suspect the errors to display heteroskedasticity across panels and, possibly, to be serially correlated.

We therefore performed a test for heteroskedasticity on a simple pooled OLS model and found it to be significant at both the sector and technological classes level[12]. We also tested for serial correlation in the error term, rejecting the null hypothesis of no autocorrelation (modified Bhargava et al. Durbin-Watson). We then estimate equation (4) with FGLS allowing for the errors to display heteroskedasticity across panels and AR(1) autocorrelation within panels. Sector and country dummies were also added to the specification to account for the fixed effects. Finally, as in the static analysis performed in the previous section, we also estimate the model with a quadratic relationship between the technological specialization index and the structural variables.

The estimated coefficients from our dynamic specification (eq. 4) show that the knowledge accumulation variables are in general statistically significant and importantly affect the technological specialization of countries. LINKCIT is statistically different from zero for all sectors. This reinforces the results of Section 3 that high knowledge flows (in terms of citations) with specialised technological classes are associated with higher technological advantages in the citing class. Again, as in the previous section, the value of the estimated coefficient is particularly high for the Chemical sector. Consider now the results related to knowledge accumulation from firms' research activities and public institutions. They show that the public and private research has an important effect on the patterns of technological specialization in particular in the Chemical and Electronic sectors. This result is in line with our expectations because these sectors have a knowledge base closer to applied and pure science, hence we expect spillovers from research in the public sector and universities to be more effective.

The variable approximating the quality of the research performed in public institutions and universities, INTCIT, displays a positive and statistically significant relationship with technological specialization in Chemicals and Electronics. In the same way, the five-year cumulated R&D advantage index (RRA5) is also statistically significant for the technological classes belonging to Chemicals and Electronics, while RRAS is significantly positive only in the Electronic sector. It's interesting to note that RRAS is not statistically different from zero for the Chemical Sectors. This suggests that the cumulated knowledge capital in different sectors may be subject to different depreciation rates and, therefore, in the long run, there can be sector-specific measurement errors, which affect the regression results. If it was the case that Chemicals had a depreciation rate of knowledge capital lower than that of Electronics, we would then underestimate the effect of knowledge capital accumulation in the chemical classes.

It's worthwhile noting that none of the knowledge variable related to research activities is significantly positive in the Machinery sectors. This emphasizes that there are important differences in the determinants of technological specialization across sectors related to the different characteristics of the sectoral knowledge base.

[12] The Cook-Weisberg test for heteroskedasticity always rejects the null of constant variance at the 1 percent level of significance.

For the technological classes in the Machinery sector, local knowledge flows and export specialisation seem to be much more associated with the technological specialization of countries.

We find a statistically significant relationship between a lagged value of trade specialisation (RCAN(-1)) and technological specialization. We propose that high levels of export and trade specialization in specific technological classes signal profit opportunities, foster best practice techniques and learning and, in turn, affect technological specialization. This effect is particular strong in the Machinery sector where the estimated coefficient is twice and four times respectively the correspondent effects in the Chemical and Electronic sector.

Our results confirm also the relevant degree of past-dependency of patterns of technological specialisation and its cumulative character. This is a widely acknowledged evidence discussed thoroughly elsewhere (Laursen, 2000; Mancusi, 2000; Pavitt, Patel, 1994; Archibugi, Pianta, 1992). Again, as in Section 3, it can be noted that the degree of persistency is relatively higher for the technological classes in Electronics and Machinery and lower in Chemicals.

With regard to the Schumpeterian variables results are less clear cut. First we observe, for the Chemical and Machinery sectors, that technological advantages are positively associated with the index of innovative concentration (HERFij). This relation is non linear in the Chemical technological classes where the squared term for HERFij is significantly different from zero with a negative sign. This implies that a core of strong innovators is beneficial for technological specialisation only up to a certain threshold. Concentration does not seem to be associated with technological specialisation in the Electronic sectors where both HERF and HERF*HERF are not statistically different from zero.

In this dynamic specification RTANij does not display, in general, a significant relationship with ENTRYij. With two exceptions, though: first in the chemical sector, the estimated relationship between concentration and technological advantages is not independent from the rate of entry of innovative firms. The interaction term (ENTRYij*HERFij) between concentration and entry shows that the marginal effect of higher innovative concentration on technological advantages is decreased when entry is higher. In these technological classes if there are new innovators competing with the incumbent firms, the relationship between concentration and technological specialization turns out to be lower. Secondly, in the Electronics Sector we observe a negative impact of ENTRY on RTAN and a significantly positive estimated coefficient for the interaction term (ENTRYij*HERFij). In section 3 we observed a cross-section positive association between concentration, entry and technological specialization in Electronics. Here we find it to be true only for specific combinations of the two values. This is the case when concentration and entry have a positively impact on technological specialization only if they jointly occur. It can be argued that in Electronics if we have sparse new innovators without an established oligopolistic core this is associated with an unspecialized technological class. Conversely if entry is associated with a few strong and persistent innovative firms this enhances technological specialization.

These results are not radically different from the ones we have in Section 3. They confirm the importance of having a core of few strong innovators and suggest to be cautious in interpreting the relationship between innovative entry and technological specialization. In general the relation between market structures and technological specialization is non-linear and does not seem to be an invariant across sectors. On the contrary specific combination of innovative firms behaviours and structures have different impacts according to the sector considered.

The careful reader would have noticed by now that the presence of a lagged dependent variable in the specification and the large cross-sectional dimension coupled with the short time dimension of our panel should have lead us to estimate the model with the techniques developed by Arellano and Bond (1991). Several difficulties arise in trying to estimate our model using the GMM estimator of Arellano-Bond.

First, in all our trials the Sargan test of over-identifying restrictions rejected the hypothesis of the model being correctly specified. This might be a consequence of our model being characterized by heteroskedasticity. In fact, Arellano and Bond (1991) found evidence that the one-step Sargan test over rejects in the presence of heteroskedasticity. However, only in the case of a homoskedastic error term does the Sargan test have a known (chi-squared) distribution, therefore we have no way to check for the reliability of the identifying restrictions under the opposite assumption.

A second problem arises from the use of the moving averages in the calculations of some of our variables. These induces second-order (and higher) autocorrelation in the differenced residuals, which implies that the estimates are inconsistent.

Overall, the difficulties in employing a certainly more appropriate estimation technique arise because the specification of the model is not strongly theoretically founded. Only a fully developed theory would allow us to understand (and test) the role of the variables involved and could guide us in correctly using them as instruments for the lagged dependent variable. This is an issue we want to address in the future.

5. Conclusions

In this paper we investigate the determinants of international technological specialization focusing on a set of variables related to knowledge accumulation, profit opportunities and the structure of innovative activities. Using both a cross-section and a dynamic framework, we show that many variables associated with the different sources and ways of knowledge accumulation affect the patterns of technological specialization and its dynamics, consistently across countries and sectors. We show that the technological specialization of a country in a technological class is associated with the quality and direction of knowledge flows across technologies within a country. In particular, international technological specialization of a country in a specific technology is positively affected by strong local knowledge links with those technologies in which the country is internationally specialized.

Moreover R&D specialization, that is countries' research trajectories and the resulting accumulated knowledge capital, significantly influences technological specialization, not the least because R&D increases the ability of firms to learn and to absorb information developed outside the boundaries of the firm. We also show that in specific technological classes, in particular within Chemicals and Electronics, the quality of the research output by public institutions and universities is an important factor in guiding and enhancing technological specialization. Finally, in the cross-section specification, a greater amount of country-level technological co-operation can be associated to greater technological specialization.

Taken together these results indicate that knowledge accumulation is a key factor affecting specialization. They support the currently used notion of national systems of innovation and suggest that the notion of inter-sectoral spillovers has to be disentangled in a more detailed way and given a more precise meaning.

We also considered the role of innovative market structures on technological specialization. Results here are less unequivocal. From a cross-sectional point of view, the positive role of both concentration and entry for international technological specialization suggests that specialization is associated to the presence of both a core of persistent innovators and a fringe of entrants that bring new ideas, new products and new processes in a sector. This relationship appears strongly non linear and it turns out that technological specialization is positively associated with concentration only if it is not associated with a high share of new innovative firms. Conversely technological specialization appears to positively affected by entry if barriers are low and in presence of a low degree of innovative concentration.

With regard to the Schumpeterian variables results are less clear cut in the dynamic specification, especially for what concerns the relationship between countries' technological specialization and entry. However, in the Chemical and Machinery sectors technological advantages remain positively associated with the index of innovative concentration and implies that a core of strong innovators is beneficial for technological specialization, but only up to a certain threshold.

Our results confirm also the relevant degree of past-dependency of patterns of technological specialization and its cumulative character. Secondly, we found a statistically significant relationship between a lagged value of trade specialization and technological specialization. We suggest that high levels of export and trade specialization in specific technological classes signal profit opportunities, foster best practice techniques and learning and, in turn, affect technological specialization.

Tab. 1: Estimation of equation (1).

	Chemicals	*Electronics*	*Mechanics*
Linkcit	0.34**	0.25**	0.16*
	(4.02)	(3.5)	(1.7)
Herf	0.36*	0.38*	0.52*
	(2.1)	(2.06)	(1.9)
Entry	0.21	0.49*	0.35+
	(1.01)	(2.1)	(1.5)
Copatf	0.15*	0.01	0.23*
	(2.4)	(0.19)	(1.8)
RTA(-1)	0.64**	0.76**	0.75**
	(14.7)	(19.4)	(14.8)
Herf*Entry	-0.67**	-0.25	-1.07**
	(-2.7)	(-0.8)	(-2.7)
Entry*Entry	0.01	-0.47*	-0.24
	(0.05)	(-1.8)	(-0.9)
Constant	-0.15**		
	(-2.5)		
N	523		
Adj. R^2 (a)	0.70		
X^2_{TOT}	1239.3**		
X^2_lag1	94.81**		
X^2_{SLOPE}	29.52**		

Specification (1) uses FGLS estimator with groupwise heteroscedasticity consistent variance estimator (z in parenthesis). The restriction of homogeneity of the intercept across macro sectors has been accepted. The restriction of homogeneity of the slopes across macro sectors has been rejected (X^2_{SLOPE}=29.52). X^2_lag1 test the null hypothesis that all variables except from RTA(-1) are jointly equal to zero. This hypothesis is rejected.

(a) Adj. R^2 refers to the OLS estimation.

** 99% significance level

* 90% significance level

+ 85% significance level

Table 2. Estimation of equation (4)

	Chemicals	*Electronics*	*Mechanics*	*Chemicals*	*Electronics*	*Mechanics*
rtan(-1)	0.87** (98.34)	0.95** (146.29)	0.93** (124.38)	0.87** (97.60)	0.95** (147.33)	0.93** (124.38)
rcan(-1)	0.02** (4.23)	0.01** (2.87)	0.04** (7.29)	0.02** (4.52)	0.01** (2.78)	0.04** (7.53)
Linkcit	0.09** (7.04)	0.05** (4.30)	0.06** (5.50)	0.10** (7.51)	0.04** (4.23)	0.06** (5.65)
Intcit	0.003** (1.99)	0.003** (2.54)	-0.003** (-2.26)	0.003* (1.89)	0.003** (2.55)	-0.003** (-2.25)
rra5	0.03** (2.42)	0.01** (3.19)	-0.01 (-1.06)	- (-)	- (-)	- (-)
Rras	- (-)	- (-)	- (-)	0.002 (0.16)	0.01** (2.58)	-0.02* (-1.68)
Herf	0.20** (5.08)	-0.04 (-0.91)	0.15** (1.98)	0.20** (5.22)	-0.04 (-0.90)	0.15* (1.88)
herf * herf	-0.19** (-3.61)	0.02 (0.26)	-0.18 (-1.18)	-0.20** (-3.72)	0.01 (0.23)	-0.17 (-1.11)
Entry	0.007 (0.29)	-0.04* (-1.82)	-0.004 (-0.11)	0.01 (0.60)	-0.04** (-1.96)	-0.002 (-0.06)
Entry*entry	0.009 (0.42)	0.03 (1.53)	-0.003 (-0.09)	0.004 (0.18)	0.03 (1.58)	-0.006 (-0.19)
Entry*herf	-0.36** (-5.97)	0.15* (1.84)	-0.08 (-0.75)	-0.38** (-6.24)	0.15* (1.83)	-0.08 (-0.71)

N	3588	3588
X^2	121028.97	120482.53

All the specifications above have been estimated with FGLS, allowing for the errors to display heteroskedasticity across panels and AR(1) autocorrelation within panels. Sector and country dummies were also added to the specification to account for the fixed effects.

** 95% significance level
* 90% significance level

Bibliography

Amable, B., Verspagen B., (1995); The Role of Technology in Market Share Dynamics, *Applied Economics*, v. 27, pp. 197-204.

Amendola G., Dosi G., Papagni E. (1993); The Dynamics of International Competitiveness, *Weltwirtshaftliches Archiv*, v.129, pp. 451-471.

Amendola, G., Guerrieri, P., Padoan, P.C. (1998). International Patterns of Technological Accumulation and Trade, in Archibugi, D., Michie J. (eds.) *Trade, Growth and Technical Change*, Cambridge University Press. Ch. 7.

Amiti M. (1999); Specialisation Patterns in Europe, *Weltwirtshaft Archiv*, 135(4), pp. 574-593.

Archibugi, D. Pianta M. (1992); Specilization and Size of Technological Activities in Industrial Countries: The Analysis of Patent Data, *Research Policy*, 21, pp. 79-93.

Archibugi, D. Pianta M. (1994); Aggregate Convergence and Sectoral Specilization in Innovation. *Journal of Evolutionary Economics*, 4, pp. 17-33.

Arellano and Bond (1991); Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations, *Review of Economic Studies*, 58, pp. 277-297.

Audretsch, D. (1996), *Innovation and Industry Evolution*, MIT Press, Cambridge

Aw, B. Y., Sukkyun Chung, Roberts, M.J., (2000); Productivity and Turnover in the Export Market: Micro-level Evidence from the Republic of Korea and Taiwan (China), *The World Bank Economic Review*, v. 14, 1, 65-90.

Balassa, B. (1965); Trade Liberalisation and Revealed Comparative Advantage. *The Manchester School of Economic and Social Studies*, n. 33.

Brasili A., Epifani P., Helg R. (1999); On the Dynamics of Trade Patterns, *Liuc Papers*, N. 61.

Breschi, S., Malerba, F., Orsenigo, L. (2000). Technological Regimes and Schumpeterian Patterns of Innovation, *The Economic Journal*, 110, pp. 388-410.

Bell, M., Pavitt K. (1993); Technological Accumulation and Industrial Growth. Contrasts between Developing and Developed Countries, *Industrial and Corporate Change*, 2, 157-210.

Cantwell, J. (1989); *Technological Innovations and Multinational Corporations*, Blackwell, Oxford.

Cantwell, J. (1995); The Globalisation of Technology. What Remains of the Product Cycle Model ?. *Cambridge Journal of Economics*, 19(1), pp.155-174.

Cohen, W., Levinthal, D. (1989); Innovation and Learning the Two Faces of R&D. *The Economic Journal*, 99, 569-596.

Cooke, P. (1998); *Regional Systems of Innovations. The Roles of Governances in a Globalized World.* UCL Press, London.

Dahmen E. (1989), Development blocks in industrial economics, in B. Carlsson. (ed.) *Industrial dynamics*, Kluwer Academic Publishers. Boston.

Dalum, B., Laursen, K., Villumsen, G. (1998). Structural Change in OECD Export Specialisation Patterns: De-specialisation and 'Stickiness'. *International Review of Applied Economics*, v. 12, n. 3, pp. 423-443.

De Liso, N. Metcalfe J. S. (1996); On Technological Systems and Technological Paradigms. Some Recent Developments in the Understanding of Technological Change, in Helmstädter, Perlman, E. (eds), *Technological Progress and Economic Dynamics*, University of Michgan Press, Ann Arbor.

Dosi, G. (1997); Opportunities, Incentives and the Collective Patterns of Technological Change, *The Economic Journal*, 107, pp.1530- 1547.

Dosi, G. (1988); Sources, Procedures and Microeconomic Effects of Innovation. *Journal of Economic Literature*, Vol. 26, pp. 1120-1171.

Dosi, G., Pavitt, K., Soete, L. (1990). *The Economics of Technical Change and International Trade*, Harvester Wheatsheaf, Hertfordshire.

Edquist C., (1997) (ed.), *Systems of Innovation. Technologies, Institutions and Organizations*. Pinter, London.

Fagerberg J. (1992); The Home-Market Hypothesis Re-examined: The Impact of Domestic User-Producer Interaction on Export Specialisation, in: Lundvall B.-A. (ed.); *National System of Innovation. Towards a Theory of Innovation and Interactive Learning*. Pinter. London. Ch. 11, pp. 226-241.

Geroski P. (1995), What do we know about entry?, *International Journal of Industrial Organization*, 4, 421-440

Greenhalg C., (1990); Innovation and Trade Performance in the United Kingdom, *The Economic Journal*, v.100, pp. 105-118.

Grupp, G, Munt, H. (1995); Konkordanz zwischen der internationalen Patent und Warenklassification, Fraunhofer-ISI. Karlsruhe.

Hall, B., Mairesse, J. (1995); Exploring the Relationship between R&D and Productivity in French Manufacturing Firms, *Journal of Econometrics*, 65, 263-293.

Howells J. (1999); Regional Systems of Innovation? in Archibugi, D., Howells, J. and Michie, J. (eds.); *Innovation Policy in a Global Economy*, Cambridge University Press, Cambridge. Ch. 5, pp.67-93.

Jaffe A.B., Trajtenberg M., Fogarty M.S. (2000); The Meaning of Patent Citations: Report on the NBER/Case-Western reserve survey of Patentees. *NBER Working paper series*, n. 7361

Laursen K. (2000); Do Export and Technological specialisation Patterns co-evolve in Terms of Convergence or Divergence ? Evidence from 19 OECD Countries, 1971-1991. *Journal of Evolutionary Economics*, v. 10, pp. 415-436.

Laursen, K., Drejer I. (1999); Do Inter-Sectoral Linkages Matter for International Export Specialisation ? *Economics of Innovation and New Technology*, 8, pp. 311-330.

Lundvall B.-A. (ed.) (1992); *National System of Innovation. Towards a Theory of Innovation and Interactive Learning.* Pinter. London.

Magnier, A..- Toujas-Bernate, J. (1994); Technology and Trade: Empirical Evidences for the Major Five Industrialized Countries, *Weltwirtshaftliches Archive*, v.130, pp. 494-520.

Malerba F. (2000); Sectoral System of Innovation and Production. *Research Policy.* Forthcoming.

Malerba, F. (1992); Learning by Firms and Incremental Technical Change, *The Economic Journal*, 102, pp. 845-859.

Malerba F., Montobbio, F. (2000); Knowledge Flows, Structure of Innovative Activity and International Specialisation, Working Paper CESPRI. N. 119.

Malerba F. Orsenigo L. (2000), Knowledge, innovative activities and industry evolution, *Industrial and Corporate Change*, fortcoming.

Malerba F. Orsenigo L. (1999), Technological entry, exit and survival: an empirical analysis of patent data, *Research Policy*, 28, p. 643-660.

Malerba F., Orsenigo L. (1997); Technological Regimes and Sectoral Patterns of Innovative Activities, *Industrial and Corporate Change*, v. 6(1), pp.83-117.

Malerba F. Orsenigo L. (1996); Schumpeterian Patterns of Innovations are Technology Specific, *Research Policy*, 25, pp. 451-478.

Malerba F., Orsenigo L. (1993); Technological Regimes and Firm Behaviour, *Industrial and Corporate Change*, v. 2, pp. 45-74.

Malerba F., Orsenigo L. Peretto P. (1997); Persistence of Innovative Activities, Sectoral Patterns of Innovation and International Technological Specialisation. *International Journal of Industrial Organisation.* V. 15, pp. 801-826.

Mancusi, M. (2000); The Dynamics of Technology in Industrial Countries. Working Paper CESPRI, n. 118.

Massini, S. (1996); Inter-sectoral flows of Technology: an International Comparison of Technological Specialisation Profile. Mimeo.

Montobbio F. (1999); Sectoral Specificity in th Relation between Technology and Market Share Dynamics. *IRER Working Paper*, n. 18.

Montobbio F. (2000); National System of Innovation. A Critical Survey. *ESSY Working Paper*, n. 2.

Nelson R. (1995), Recent evolutionary theorizing about economic change, *Journal of Economic Literature*, v.33,

Nelson R.R. (ed.), (1993) *National Innovations Systems: A Comparative Study*, Oxford, Oxford University Press.

Nelson, R.R. Winter S. (1982); *An evolutionary Theory of Economic Change*, The Belknap Press, Cambridge (Mass.).

Nelson R., Wright G. (1992); The Rise and Fall of American Technological Leadership: The Postwar Era in Historical Perspective, *Journal of Economic Literature*, 30, 1931-1964.

OECD (1999); Analytical Business Enterprise R&D (ANBERD) Database, OECD Paris.

Patel P. (1995); Localised Production of Technology for Global Markets, *Cambridge Journal of Economics*, 19(1), pp.141-153.

Patel P., Pavitt K., (1994); Uneven (and Divergent) Technological Accumulation among Advanced Countries: Evidence and a Framework of Explanation. *Industrial and Corporate Change*, v.3, n.3, pp. 759-787.

Patel P., Pavitt K., (1996); Patterns of Technological Activity: their Measurement and Interpretation, in Stoneman P. (ed.), *Handbook of the Economics of Innovation and Technological Change*. Blackwell. Oxford. Cap. 2, pp. 14-51.

Pavitt K. (1984), Sectoral patterns of technical change: towards a taxonomy and a theory, *Research Policy*, 13, p.343-373.

Scherer F.M. (1982); Inter-industry Technological Flows and Productivity Growth, *Review of Economic and Statistics*. v. 64, pp. 627-634.

Soete, L. G. (1981); A General Test of Technological Gap Trade Theory, *Weltwirtshaftliches Archiv*, band 117, pp. 638-650.

Teece, D.J. (1988); Technological Change and the Nature of the Firm, in G. Dosi et al. (quoted) (ed.), *Technical Change and Economic Theory*, Frances Printer, Londra. pp. 256-281.

Winter S. (1987); Knowledge and Competence as Strategic Assets, in D.J. Teece (ed.), *The Competitive Challenge*, Ballingen, Cambridge (Mass.), pp. 159-184.

World Bank, (1993); *The East Asian Miracle*. Oxford University Press, New York.

Appendix:

R&D Expenditures concordance tables.

R&D expenditures form ANBERD (OCSE, 1999) are classified according to 'ISIC revision 2'. In order to assign R&D values to our technological classes (see Tab. A.2) we had to build concordance tables. Our classes come from the Fraunhofer Concordance (Grupp, Munt, 1995) between IPC Classification and SITC Rev. 3 classification and are much more dis-aggregated than those in the ISIC Rev. 2. Accordingly the same ISIC class had to be assigned to more than one technological class.

Our classes are built around a group of SITC Rev. 3 classes and, in turn, the same SITC class could be associated to more than one ISIC Rev. II class. As a result the problem to solve is how to associate some of our technological classes to many ISIC Rev. 2 classes (via SITC Rev. 3). We solved the problem calculating the weight, in terms of export, of each SITC class and, secondly, applying the weight to the corresponding ISIC classes. In particular if a SITC class weighted more than 0.7 we assigned to the Fraunhofer class the corresponding ISIC R&D value. If there was a secondary SITC class with a weight greater than 0.3 we assigned to the Fraunhofer class a weighted average of the ISIC R&D values.

Note that we applied these criteria separately to each of the countries in our dataset; as a result we have different concordance tables for different countries. Concordance Tables for all the six countries are available from the authors upon request.

Tab. A.1: Correlation matrices:

TOTAL (n=523)

	Herf	Entry	Copatf	Linkcit
Herf	1,0000			
Entry	0,24	1,0000		
Copatf	0,06	-0,11	1,0000	
Linkcit	-0,008	0,06	0,07	1,0000

CHEMICAL (n=187)

	Herf	Entry	Copatf	Linkcit
Herf	1,0000			
Entry	0,42	1,0000		
Copatf	0,04	-0,05	1,0000	
Linkcit	-0,07	-0,01	0,06	1,0000

ELECTRONICS (n=170)

	Herf	Entry	Copatf	Linkcit
Herf	1,0000			
Entry	0,14	1,0000		
Copatf	0,06	-0,1	1,0000	
Linkcit	-0,09	0,08	0,09	1,0000

MACHINERY (n=166)

	Herf	Entry	Copatf	Linkcit
Herf	1,0000			
Entry	0,1	1,0000		
Copatf	0,27	-0,2	1,0000	
Linkcit	0,03	0,11	0,12	1,0000

Tab. A.2: The List of Technological Classes.

CHEMICALS:

1) chem101	= Starch
2) chem102	= Proteins
3) chem111	= Explosives, gunpowder
4) chem112	= Fuses, ignition chemicals
5) chem113	= Pyrotechnique articles, fireworks
6) chem114	= Matches
7) chem121	= Additives for lubricating oil, corrosion inhibitors
8) chem122	= Liquids for hydraulic brakes, anti-freezing compounds
9) chem123	= Lubricants, emulsions for grease, petroleum sulfonate, artificial graphite emulsion
10) chem131	= Gas cleaning
11) chem132	= Catalysts
12) chem133	= Additives for metals
13) chem134	= Benzoles, naphts
14) chem135	= Electronic and electrotechnical chemical compounds
15) chem136	= Chemical substances for constructions
16) chem137	= Chemicals for fire extinguishers, liquid polychlor dipheniles
17) chem14	= Artificial and natural caoutchouc
18) chem15	= Natural polymers
19) chem16	= Plastic trash
20) chem17	= Plastic products
21) chem21	= Anorganic chemical compounds
22) chem22	= Anorganic oxygen compounds
23) chem23	= Anorganic sulphur compounds
24) chem24	= Other metal salts
25) chem25	= Other anorganic chemical products
26) chem26	= Radioactive substances
27) chem31	= Synthetic textile fibres
28) chem32	= Artificial textile fibres
29) chem33	= Trash
30) chem41	= Organic oils and fats
31) chem42	= Wax
32) chem43	= Artificial wax
33) chem44	= Chemical products of woodor resins
34) chem51	= Hydrocarbons
35) chem52	= Alcohol
36) chem53	= Carbon acid
37) chem54	= Compounds with nitrogen function
38) chem55	= Organic-anorganic compounds
39) chem56	= Lactam, other heterocyclic compounds
40) chem57	= Sulfamide
41) chem58	= Ether, alcohol peroxide
42) chem61	= Synthetic organic colours and varnishes
43) chem62	= Tanning agents and paint extracts
44) chem63	= Colours, varnishes, pigments
45) chem64	= Glazes, sealing compounds
46) chem71	= Vitamins, provitamins, antibiotics
47) chem72	= Hormons and derivatives
48) chem73	= Micro-organisms, vaccines
49) chem74	= Reagents and diagnostics
50) chem75	= Other special medicines
51) chem76	= Other pharmaceutical products
52) chem77	= Cosmetics (no soaps)
53) chem81	= Etheric oils and perfumes
54) chem82	= Soaps
55) chem83	= Detergents

56) chem84 = Ski-wax, furniture polishes
57) chem91 = Fertilisers
58) chem92 = Insecticides
ELECTRONICS:
1) elek10 = Ignition cables, electrical cars
2) elek11 = Small electrical engines, electrodes
3) elek11b = Portable electrical tools
4) elek12 = Motors, electrical engines and electrodes
5) elek12b = Magnetic tapes
6) elek13 = Choke coils, converters, transformers
7) elek13b = Traffic lights, etc.
8) elek14 = Generators and equipment
9) elek14b = Particles accelerator
10) elek15 = Transformers
11) elek15b = Lasers
12) elek21 = Fridges (for home and industry), air conditioning
13) elek22 = Washing machines, dryers, dish washers
14) elek23 = Electrical shavers, hair-cutting machines, hoovers
15) elek24 = Electric heating
16) elek31 = Computers and equipments
17) elek32 = Computer chips and equipments
18) elek33 = Photocopying machines and equipments
19) elek34 = Type-writers and other office devices
20) elek41 = TV, radio, TV-cameras, video-cameras, antennas, oscilloscopes
21) elek42 = Microphones, loud-speakers, recorders
22) elek43 = Telephones (no mobile phones)
23) elek44 = Radio engineering devices
24) elek511 = Circuits
25) elek512 = Resistors
26) elek513 = Switches, fuses
27) elek514 = Control panels
28) elek521 = Cables (without ignition)
29) elek522 = Insulators
30) elek53 = Capacitors
31) elek54 = Electro-magnets
32) elek61 = Electrical diagnostic devices (no X-rays)
33) elek62 = X-rays
34) elek63 = Instruments to show ionic beams
35) elek71 = Diodes, transistors
36) elek72 = Integrated circuits
37) elek8 = Batteries, accumulators
38) elek9 = Portable electrical lamps
MACHINERYS:
1) masch10 = Printing machines
2) masch11 = Steam-boiler
3) masch11b = Machines for food processing
4) masch121 = Steam-turbines for ships
5) masch122 = Steam-turbines for steam power plants
6) masch12b = Machines to process rocks, etc.
7) masch131 = Gas-turbines for aeroplanes
8) masch132 = Gas-turbines for power stations
9) masch13b = Wood processing machines
10) masch14 = Plastic processing
11) masch15 = Saws, etc.
12) masch16 = Spanlos Machine Tools
13) masch17 = Metal-working rolling mills
14) masch18 = Soldering irons, blow lamps, welders

15) masch19 = Torches, furnaces
16) masch20 = Ovens, distilling apparatuses, gas distilling
17) masch21 = Piston-drive engines for aeroplanes
18) masch21b = Pumps, centrifuges, filters
19) masch22 = Engines for cars
20) masch22b = Conveyors
21) masch23 = Engines for ships
22) masch23b = Anti-friction bearing
23) masch24 = Engines for trains
24) masch24b = Valves
25) masch25 = Packaging machines
26) masch26 = Scates
27) masch27 = Fire extinguisher, spray guns
28) masch28 = Other machines
29) masch3 = Water-turbines
30) masch4 = Nuclear power reactors
31) masch5 = Other engines
32) masch61 = Agricultural machines (without tractors)
33) masch62 = Tractors
34) masch7 = Constructions and mining machines
35) masch8 = Textile machines
36) masch9 = Paper production machines