J Evol Econ (2003) 13: 411–434
DOI: 10.1007/s00191-003-0162-z

Journal of Evolutionary Economics

Exploring factors affecting international technological specialization: the role of knowledge flows and the structure of innovative activity*

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Abstract. We define international technological specialisation (ITS) as the technological performance of a country in a specific technology relative to its overall international technological performance. This paper uses patent applications and patent citations at the European Patent Office for five countries (US, UK, Italy, France, Germany) from 1989 to 1994 for 135 technological classes in three industrial sectors (Chemicals, Electronics and Machinery). It shows that ITS is significantly persistent and is affected by the direction of cross-sectoral knowledge spillovers within countries. In addition, the paper shows that the concentration of innovative activities, the emergence of new innovators and technological co-operation positively affect ITS. Some differences across sectors emerge.

Key words: Technological specialisation – Knowledge spillover – Market structure

JEL Classification: O30, L10

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* We are grateful to Giorgio Rivero and Dieter Urban for valuable research assistance. We are indebted to Paul Geroski, Stefano Breschi, the participants to the Eighth International Schumpeter Conference (Manchester, 2000) and two anonymous referees and the editors of this Journal for their insightful suggestions. Citations data were provided to us by Bart Verspagen. The usual disclaimer applies. This paper originally developed as 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)]. It has also benefited from The Short-term Mobility Program by Italian CNR (Prot. 031883) and from the coordinated Projects of Italian CNR.
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1 Introduction

This paper examines key factors affecting international technological specialisation. In the last decade, much effort has been dedicated to understanding whether countries are undergoing processes of technological specialisation and whether this process is associated with convergence in levels of innovative activity, structures of production and export patterns (Amiti, 1999; Brasili et al., 2000; Archibugi and Pianta, 1992, 1994; Laursen, 2000). Less attention has been paid to the determinants of technological specialisation in specific activities (Archibugi and Pianta, 1994; Patel and Pavitt, 1994, 1996; Dalum et al., 1998). In this regard, the evidence about increased technological specialisation in individual fields has been linked to the role of institutional and economic factors (which are location specific), of increasing returns and of scale economies in innovation and production (Archibugi and Pianta, 1994; Dalum et al., 1998; Amiti, 1999).

This paper concentrates on two factors affecting international specialization: within-country knowledge linkages among technologies and the structure of innovative activities. With respect to this second aspect, the paper provides an exploratory attempt to assess whether concentration, entry of new innovators and technological co-operation are related to specialisation in individual technological fields. While knowledge linkages are considered to have a positive affect on specialization, more controversial is the role of the structure of innovative activity. The empirical analysis is done for five countries (US, UK, IT, FR, DE) at a disaggregated level of technological classes in Electronics, Machinery and Chemicals from 1989 to 1994.

The paper is organised as follows. In Section 2, the concept, measure and determinants of international technological specialisation are discussed. Then in Section 3, the relationship between within-country knowledge flows and international specialization is examined, while in Section 4, the association between international technological specialization and the specific structure of innovative activities is discussed. Section 5 describes the data used and the construction of the variables. Section 6 introduces the econometric analysis and presents the results. Finally, concluding comments are in Section 7.

2 The international technological specialisation (ITS) of countries: concept, measure and determinants

This paper examines some key factors related to the international technological specialisation of countries. We define *international technological specialisation* (ITS) as the international technological performance of a country in a specific technology relative to its overall international technological performance. Thus we claim that a country is specialized in electric heating or additives if its technological performance in these classes at the international level is higher than its overall international technological performance.

Technological specialization is related to relative advantages and not absolute ones. In principle, a country may have absolute advantages (and be more innovative) in all technologies. However, even in this case, it has relative advantages in some technologies compared to others.

How is it possible to measure the ITS of countries? In most empirical analyses, patents have been used for measuring innovation in specific technologies.[1] Using patents, one could measure the technological strength of a country by calculating the share of that country's patents to total world patents (see row (1) in Table 1). Similarly, the technological strength of a country in a specific technology can be measured by the share of that country's patents to total world patents in that technology (see row (2) in Table 1). This is an indicator reflecting absolute advantages. In fact, a country may have a very high share in all technologies, as a consequence of its high R-D expenditures in all technologies or its overall large size. For example, in 1993–1994 the US had the highest share in 9 out of the 10 technological classes displayed in Table 1 because they had high R-D expenditures in all these classes due to their large size compared to most other countries. While a country's share in a specific technology is a good indicator of absolute advantage, it does not indicate how that country is performing in a specific technological class relatively to other technological classes. For example, the US may have an absolute advantage in Insecticides and, at the same time, be relatively de-specialised in this technological field, because its international performance in other classes is higher (see Table 1).

As a result, many authors have adopted the so-called Technological Revealed Comparative Advantage index (RTA) in order to measure the ITS in a technological field.[2] RTA is the traditional Balassa indicator of revealed comparative advantage applied to innovation analysis (Balassa, 1965). It measures the share of patents granted to (or applied for by) firms and other organisations (e.g. universities and research centres) in country c in technology j on total world patent in technology j, divided by the share of total patents granted to (or applied for) firms and other organisations in country c to total world patents.

$$\mathrm{RTA}_{cj} = \frac{p_{cj}}{\sum_c p_{cj}} \Bigg/ \frac{\sum_j p_{cj}}{\sum_j \sum_c p_{cj}},$$

where p_{cj} denotes the total amount of patent applications (granted) in technological class j by country c. This index has a weighted average[3] equal to 1 and a skewed distribution, taking values between zero and infinity. To perform regression analyses, it is preferable to define a modified and symmetric version of this index:[4]

$$\mathrm{RTAN}_{cj} = (\mathrm{RTA}_{cj} - 1)/(\mathrm{RTA}_{cj} + 1)\ . \tag{1}$$

RTAN is a monotonic transformation of RTA that is better suited to an econometric analysis of ITS because it is symmetric and reduces the value of extreme

[1] The limitations of the use of patent statistics as indicators of innovative activities have been widely discussed and acknowledged. They refer to the different propensity to patent across sectors and to the difference between patents in their degree of technological novelty and economic utility (Pavitt, 1985; Griliches, 1990; Grupp, 1990).

[2] For example, the Technological Revealed Comparative Advantage index has been used by Soete (1981); Patel and Pavitt (1994), Archibugi and Pianta (1992).

[3] $\sum_j \varpi_j \mathrm{RTA}_{cj} = 1; \varpi_j = \frac{\sum_c P_{cj}}{\sum_j \sum_c p_{cj}}$

[4] See Grupp (1994) and Laursen (2000) for a discussion.

Table 1. Countries patent shares at national and sectoral levels and international technological specialisation in the 10 largest technological classes in the period 1993–1994

	Germany	France	Italy	UK	US
(1)	0.26	0.11	0.05	0.08	0.50
Heterocyclic compounds					
(2)	0.29	0.10	0.05	0.14	0.40
(3)	0.06	−0.04	0.05	0.28	−0.10
Micro-organisms, vaccines					
(2)	0.09	0.09	0.02	0.10	0.70
(3)	−0.50	−0.11	−0.40	0.09	0.17
Insecticides					
(2)	0.29	0.10	0.05	0.14	0.41
(3)	0.04	−0.03	0.05	0.28	−0.09
Computers and equipment					
(2)	0.09	0.09	0.02	0.04	0.76
(3)	−0.47	−0.13	−0.42	−0.30	0.21
TV, radio et al.					
(2)	0.21	0.16	0.04	0.09	0.50
(3)	−0.12	0.19	−0.07	0.06	0.00
Telephones					
(2)	0.20	0.12	0.03	0.09	0.56
(3)	−0.15	0.05	−0.21	0.03	0.06
Cables					
(2)	0.24	0.18	0.03	0.06	0.49
(3)	−0.05	0.24	−0.25	−0.15	0.00
Diodes and transistors					
(2)	0.14	0.06	0.06	0.04	0.71
(3)	−0.32	−0.27	0.08	−0.37	0.18
Conveyors					
(2)	0.42	0.08	0.10	0.07	0.32
(3)	0.23	−0.15	0.36	−0.08	−0.21
Textile machines					
(2)	0.34	0.10	0.10	0.06	0.40
(3)	0.12	−0.06	0.33	−0.11	−0.11

(1) Country patent share
(2) Country patent share in the technological class
(3) Revealed technological advantage (RTAN)

observations; it has values that belong to the [–1,1] set. $\mathrm{RTAN}_{cj} > 0(\mathrm{RTAN}_{cj} < 0)$ means that country c is relatively specialised (de-specialised) in class j. Table 1 shows country patent shares at the national and the sectoral levels (row (1) and (2)) and the RTAN values in the 10 largest technological classes of our sample in the period 1993–1994.

The economic analysis of ITS has focused mainly on testing whether countries become increasingly technologically specialised. Based on specialisation indexes built upon patent grants and patent applications in the US and Europe, evidence shows that countries become more specialised and become increasingly less similar in their technological profile (Cantwell, 1991; Patel and Pavitt, 1994; Archibugi and Pianta, 1992, 1994). However, recent work shows that constraints on technological trajectories become less binding over time, and there is a significantly high degree of mobility across technological classes (Laursen, 2000; Mancusi, 2001), although the reasons for this are unclear.

One area of research that is rather unexplored is the theoretical and empirical explanations of the patterns of ITS of countries. In this respect, one could start from the remark that technologies are characterized by different knowledge bases and specific learning processes. Therefore, they differ very much in terms of factors affecting their advancements. Science-based technologies may be more related to science and R-D than mechanical industries, which in turn are more related to learning by doing and vertical linkages. Pavitt's taxonomy (1984) is a good example of differences across technologies and sectors in the factors affecting progress and in the way innovative activity is organized. Technologies may also differ in terms of the relevance of basic research and skills required for their advancement. Different national innovation systems (Nelson, 1993) with differences in skills and type of human capital, capabilities in scientific and technological areas by universities and research organizations, or national public policies targeting technologies or scientific fields may affect progress in some specific technologies. Britain with Mechanicals in the XVIII century, Germany with Chemicals in the XIX century and the US with Electronics and Biotechnology (Freeman and Soete, 1999; Mowery and Nelson, 1999) are good historical examples of how specific national innovation systems may have institutions that favour some technologies more than others.

In addition, the presence of specific firms and the triggering of cumulative learning may generate idiosyncratic knowledge and firm-specific advantages in certain technologies. The competence-based theory of the firm has strongly emphasised the cumulativeness of learning, knowledge and advantages (Nelson and Winter, 1982; Teece, 1988; Dosi, 1997). Specific firms with the appropriate competences may, with time, build up technological advantages that allow their country to specialise in a specific technology. This is often the result of first mover advantages in the international arena. The example of the US specialization in mainframe computers due to the fact that IBM was located within the US is a case in point.

Here we will concentrate on two factors: knowledge flows and the structure of innovative activities. We study whether knowledge interdependencies among technologies within countries affect ITS. We also analyse the structure of innovative activity that is conducive to high innovativeness and therefore goes together with ITS. In general, while knowledge flows could be interpreted as a factor affecting ITS, the structure of innovative activities may be seen more appropriately as a dimension associated with ITS, and not a determinant per se.

3 The relationship between domestic knowledge flows and international technological specialization

We propose that knowledge spillovers and knowledge linkages within countries may diffuse specialization from a specific technology to others, all within national boundaries. The reason is that knowledge associated with a technological innovation can be used by other economic agents in different technological fields. Agents do not always pay a price for it because some pieces of knowledge are codified and transferable and become public goods. In this paper, we focus on the spillovers that derive from knowledge[5] produced by innovators in a specific country and that affect the innovative activities of other innovators in different technological fields within the same country.

The economic analysis has recently tried to track the technological direction of knowledge spillovers and to evaluate the way in which innovation activities in specific technological fields use knowledge produced in other technological fields (e.g. in UK, inventors in the cosmetics industry use knowledge produced in the detergent industry and vice versa, as documented below). Recent attempts at measuring knowledge linkages and at constructing a proximity index between technological fields show that intersectoral spillovers play a relevant role in explaining some economic variables such as the growth of total factor productivity or export performance (Mohnen, 1997; Verspagen, 1997; Laursen and Drejer, 1999; Cincera and van Pottelsberghe de la Potterie, 2001). Various methodologies may be adopted to measure technological proximity: input-output tables, primary and secondary technological classifications of patent data, citations of patents and innovation counts are some examples.[6] As explained in Section 5, this paper uses patent citations because they are not only able to identify the proximity between technological classes but they are also a direct vehicle of knowledge spillovers. Moreover, they allow the precise tracking of knowledge flows at a very detailed level of technological disaggregation.

A second issue concerns the geographic extension of the knowledge spillover. Recent econometric evidence suggests that the geographical dimension is very important [7] for innovation activities. It is claimed that there are strong linkages between innovative actors in the same region and that, in particular in high tech industries, knowledge spillovers from scientific and technological activities contribute to higher rates of innovation and productivity growth within geographically bound areas. In particular, the analyses of knowledge spillovers that use patent citations emphasise that citations are more likely to be domestic (Jaffe et al., 1993; Maruseth and Verspagen, 1999; Verspagen and Schoenmakers, 2000).

Accordingly, we claim that specialization in a specific technology is positively affected by the knowledge links between that technology and the technologies in which the country is specialised. Through these knowledge links, a country will be able to benefit from its specialisation in other technologies. A key assumption

[5] There are two overlapping types of spillovers deriving from research activities: rent spillovers and knowledge spillovers. Rent spillovers are embedded in the purchased inputs which are not priced at the user value. Knowledge spillovers are related to the knowledge produced in the innovation process and are not necessarily linked to any economic transaction (Griliches, 1979; Sherer, 1982)

[6] A special issue of *Economic Systems Research* including papers by Mohen (1997) and Verspagen (1997) is dedicated to the issue of the measurement of intersectoral R&D spillovers and their impact on total factor productivity. Also Laursen and Drejer (1999), Massini (1996), Jaffe (1986, 1988), and Sherer (1982) analyse the impact of intersectoral spillovers on various aspects of the economic activities.

[7] This literature has been recently surveyed by Feldman (1999) and critically by Breschi and Lissoni (2001).

is that these benefits will mainly be internal to the country through the working of local externalities and spillovers.

4 The association of international technological specialization with a specific structure of innovative activity

ITS may be related to a specific structure of innovative activities. The reasoning may be broken in two parts. First, one may start from the recognition that the structure of innovative activities affects the rate of technological change. This could be broadly related to the old debate about market structure and innovation. It has been proposed that, up to a certain level of concentration (or up to a low entry rate), higher concentration (lower entry) increases innovation[8] (Dasgupta and Stiglitz, 1980; Nelson and Winter, 1982). However, a very high level of concentration reduces the rate of innovation, because rivalry is too limited and the inertia of the monopolist is greatly increased. Since the work of Dasgupta and Stiglitz (1980) and Nelson and Winter (1982), theoretical models of market structure and innovation have added an additional element to the previous reasoning that shows convincingly that the relationship between market structure (in terms of seller concentration) and R-D intensity or rate of innovation is endogenous.

From the previous discussion, one could claim that ITS may be associated to a specific structure of innovative activity: a rather concentrated structure with a core of major innovators that innovate continuously and a fringe of new innovators that bring dynamism and variety into the technology.[9] In addition, the structure of innovative activity associated with ITS is the outcome of other key dynamic processes that may be related to firms' R-D investments, followed by first mover advantages and by the accumulation of knowledge over time. Finally, chance may generate innovative advantages, which, if protected, may last for some time and generate a "success breeds success" mechanism.

The most appropriate structure of innovative activity may differ from sector to sector, because the balance between the core and the fringe of innovators may differ across sectors. In technologies such as aircraft and nuclear technologies, large firms are the main drivers of change. In other technologies, such as mechanicals, small and medium size firms are the main innovators. Pavitt's taxonomy (Pavitt, 1984), shows that in some sectors – such as scale intensive ones – the patterns of innovative activities are characterized by large firms and a high concentration of innovative activity, while in other sectors – such as specialized suppliers - small and medium size firms and a less concentrated structure allowing a greater degree of entry is present. Such a distinction is also captured by the difference between

[8] With low concentration, rivalry among firms is high. Incentives to innovate increase when concentration increases because of imperfect capital markets: firms with ex-ante market power have the internal financial resources necessary to invest. But more innovation due to concentration consolidates existing concentration and leads to even higher rate of innovation if learning and technical advance have a cumulative nature.

[9] Evidence provided by Malerba and Orsenigo (1997) and by Malerba et al. (1997) suggests a positive association between ITS and concentration in innovative activities, i.e. a competitive core of persistent innovators.

a Schumpeter Mark I type of technology (characterized by "creative distruction", small innovators, new entrants and continuous turbulence) and a Schumpeter Mark II type of technology (characterized by "creative accumulation", large innovators and stability of a core of large firms) (Malerba and Orsenigo, 1996; Breschi et al., 2000).[10] Thus one may identify two key variables for the empirical analysis. One refers to concentration and a core of leading innovators. The second regards entry in terms of new innovators, who bring in new ideas, new approaches and new technologies.

Here we identify a third variable: technological collaboration. The evolutionary approach and innovation systems literatures have stressed the diversity in knowledge and capabilities among agents in innovation. Trust and the range of informal interactions and relationships among agents are necessary for developing new technologies (Lundvall, 1992; Edquist, 1997; Dosi, 1997; Montobbio, 2000). In addition, it has been emphasised that the relationships between firms and non-firm organisations (such as universities and public research centres) are very important sources of innovation and change in several sectors (Nelson, 1993; Mowery and Nelson, 1999). In uncertain and changing environments, technological collaborations emerge not because agents are similar, but because they are different. In this way, networks may integrate complementarities in knowledge, capabilities and specialisation. However, its relevance may drastically differ across technologies.

In this paper, we perform some exploratory analysis on the association between ITS and a specific structure of innovative activity, in terms of innovative concentration, innovative entry and technological collaboration. In particular, we test whether:

(a) ITS is positively related to the concentration of innovative activities. This would mean that ITS is associated with an oligopolistic core of innovators, which has accumulated knowledge and competences over time. We recognize that there could be endogeneity. Not only the oligopolistic core of innovators may be conducive to a high rate of technological change and therefore international specilialization, but ITS may also affect positively the growth of an oligopolistic core of top innovators.

(b) ITS is associated with technological entry. As previously mentioned, new entrants bring in new ideas, new technologies and new products. Some turbulence could be beneficial even in highly concentrated sectors.

(c) It could be the case that ITS is related to a combination of an oligopolistic core and an innovative fringe. Existing technologies may be exploited through the accumulation of expertise and competences and new technologies may be explored through the variety of new approaches introduced by new innovators.

(d) ITS is associated with technological collaborations. A greater amount of technological co-operation may be related to ITS 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.

[10] Some authors have linked these different patterns of innovative activities at the sectoral level with the specific features of the technological environment (Breschi et al., 2000; Malerba and Orsenigo, 1997).

(e) The above relationships are sector-specific. Since sectors differ in knowledge bases, learning regimes, productive features and institutional settings (Dosi, 1988, 1997; Malerba, 2002; Montobbio, 2003) we expect that these sectoral differences affect the relationship between the afore-mentioned variables and ITS. We will test it by analyzing chemical, electronic and mechanical technologies.

5 Data and variables

The data set is composed of patent applications (EPO/CESPRI)[11] and patent citations[12] by firms, universities and research centres in five countries: France, Germany, Italy, UK and US. Patent applications are considered in the period from 1989 to 1994. The values are averages over three sub-periods, 1989–1990, 1991–1992 and 1993–1994. We consider 135 technological classes in three industrial sectors: 61 chemical technological classes, 38 electronic technological classes and 36 machinery technological classes[13] (Grupp and Munt, 1995). Patent data are used to calculate the ITS indexes and patent citations are used to identify knowledge flows.

Knowledge flows are inherently difficult to measure. It is often problematic to assess the relevance of the source of knowledge and to evaluate the direction and the impact of the generated knowledge. In this paper, ITS is considered the source of knowledge spillover. Patent citations identify the direction of these knowledge spillovers across technologies within each country. We enquire whether knowledge spillover emanates from patenting firms and organisations and benefit other technological fields in the same country. This knowledge diffuses proportionately to the degree of technological proximity between the different technological fields within each country.

The use of patent citations as a measure of technological proximity is justified by their legal dimension, as they limit the scope of the property right in the patent claim. As emphasised by Trajtenberg (1990), the list of citations is generated through a process involving the applicant, his attorney and the examiner that generates 'the right incentives to have all the relevant patents cited, and only those' (p.

[11] CESPRI/EPO data-set has 919.451 *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 UK and US, CESPRI/EPO has 225987 patent applications. Our 135 classes, taken from Grupp and Munt (1995), cover 152.913 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 from the analysis we have excluded technological classes with a total number of patents in all countries 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.

[12] Patent Citations have been provided by Bart Verspagen. Citations are considered for the whole period (78–96). The total amount of citations is 799.038. The citations between our 135 classes are 437.752.

[13] The technological classes are listed in Grupp and Munt (1995) and are available from the authors on request. 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 Machinery.

174). As a result, patent citations can be used to trace linkages between applicants, their technological fields and their locations. These linkages can be considered to represent a knowledge spillover, since the applicant refers to a piece of previously existing knowledge and the patent builds upon the cited ones (Jaffe et al., 1993). A survey of inventors by Jaffe et al. (2000) shows that citations can be used to track knowledge flows, being a noisy signal of spillover. They show that the likelihood of knowledge spillover is significantly higher if there is a citation. At the same time, other studies show that patent citations are related to the value of the innovations and to financial market valuation of the firms who own the patent (Trajtenberg, 1990; Hall et al., 2000).

In sum, the degree of ITS can be considered an indicator of knowledge-creation in a specific field. Patent citations track the direction of knowledge spillovers within each country. As a result, a country should be relatively more specialised in the technological fields that benefit from these spillovers. We expect that a country has a higher specialisation in technological class j if it displays a higher specialisation in the classes that are cited by patents in class j.

In macro and in microeconomic empirical studies, the knowledge spillover variable is constructed in the following way (e.g. Cincera and van Pottelsberghe de la Potterie, 2001; Helpman and Coe, 1995; Jaffe, 1988; Scherer, 1984):

$$K_{cj} = \sum_{k \neq j} u_{cj}^{k} R_{ck} \tag{2}$$

R_{ck} is the variable measuring the source of knowledge in country c and class k (in our case, the degree of ITS in the field k). u_{cj}^{k} measures the technological proximity between technological classes k and j in country c.

For each country, we use patent citations to build a weighting matrix CIT, which is squared and asymmetric. We use citations from the whole period 1978–1996. Each element of the matrix $\{\mathrm{CIT}_{cj}^{k}\}$ represents the number of patent citations flowing from technology j into technology k (c signals that the matrix is specific to country c). The elements on the main diagonal $\{\mathrm{CIT}_{cj}^{j}\}$ are the number of citations that remain in the same technological class in a specific country c. These elements have been excluded in the computation of the index of technological spillover because we examine the knowledge connections between different technological classes (further illustration and examples about this type of analysis can be found in the Appendix A1).[14] If we define CIT_{cj} as the total amount of citations flowing out of technological class j in country c (the sum of the j-th row of the matrix), then

$$\mathrm{CIT}_{NODIAGcj} = \sum_{k \neq j} \mathrm{CIT}_{cj}^{k} = \sum_{k} \mathrm{CIT}_{cj}^{k} - \mathrm{CIT}_{cj}^{j} = \mathrm{CIT}_{cj} - \mathrm{CIT}_{cj}^{j}$$

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

represents the number of citations flowing out from class j with the exclusion of citations within the same technological class. Accordingly, $u_{cj}^{k} = \mathrm{CIT}_{cj}^{k} / \mathrm{CIT}_{\mathrm{NODIAG}cj}$ is the fraction of all the citations from patents in class j in country c that cite patents in class k. u_{cj}^{k} ranges between 0 to 1 depending on the intensity of the knowledge linkage between classes k and j in country c. Our modified version of the knowledge spillover index is:

$$\mathrm{LINCIT}_{cj} = \sum_{k \neq j} u_{cj}^{k} \mathrm{RTAN}_{ck}$$

$k, j = 1, ..., 111$ for technological classes,
$c = 1, ..., 5.$ for countries,

LINCIT_{cj} values belong to the $(-1, +1)$ interval. Positive values indicate that, in country c, technological class j displays strong knowledge linkages in terms of citations with sectors in which country c is specialised. Negative values indicate that technological class j is connected in country c with sectors that have a technological relative disadvantage. As a result, we expect a positive relationship between LINCIT_{cj} and RTAN_{cj} because a country should be relatively more specialised in those technological fields that benefit from spillovers deriving from other classes in which it is specialised.

If the citation matrices CIT_{cj}^{k} are all the same for all countries c, then they would represent just country-invariant technical relations. Under these circumstances, the interpretation of a statistically significant relationship between LINCIT and RTAN would be that the knowledge flows shaping ITS have a strictly technical origin and are not affected by country-specific variables. This could be tested against the null hypothesis that these knowledge flows have no effect on ITS.

Conversely, differences in the matrices across countries would indicate that, specific patterns of knowledge flows exist and guide ITS. Knowledge flows would not just be the result of technical relationships as such. CIT_{cj}^{k} would indicate that each country develops its own specific knowledge linkages.

In order to assess the differences across country between matrices, we have built the following indicators. First, for each technological class in each country, we first looked at the most cited class and then at the two most cited classes. Then, for each technological class, we compared the results across countries (e.g. in Table 3 the most cited classes by the technological field ‘Cosmetics’ are ‘Other Special Medicines’ in France and ‘Insecticides’ in UK). The results are that 19% of the 135 classes have the same most cited class (and 11% of the 135 classes have the same two most cited classes).[15]

[15] In order to evaluate whether the relevant knowledge sources for class j are dispersed across many technological classes k in each country, we calculated Herfindahl indexes and an index λ that indicates the number of classes k (for each technological class j, in each country) that received at last the 10% of citations (i.e. the amount of classes k for which $u_{cj}^{k} > 0.1$). We correlated λ between countries (across technological classes). Correlation coefficients are significantly positive but the values are not very high. The 15 correlation coefficients range from 0.18 to 0.54. Similarly, we correlated the 135 Herfindahl indexes referring to the technological classes between countries. Results show that 5 out of 15 correlation indexes are not statistically different from zero. The other 10 coefficients do not display very high values ranging from 0.17 to 0.67.

This analysis suggests that the national matrices display broad similarities in terms of general patterns and indicates the technological nature of knowledge linkages. However, they also display differences, suggesting that some relevant knowledge links are country-specific.

In order to test the role of the structure of innovative activity, we include the following three variables in the econometric specification. Our cross-sectional group i is represented by a specific technological class j in a specific country c. As a result, we have 555 cross-sectional units (111 technological classes and 5 countries) for three years.

a) HERF_{it}: the Herfindahl index in group i (class j and country c). This is obtained by squaring the patent share of each firm in each technological class and then summing those squares.[16]

b) ENTRY_{it}: the share of firms that innovate for the first time in group i. HERF_{it} and ENTRY_{it} are used in order to assess the effects of innovative concentration and innovative entry on ITS. As discussed above, a statistically significant relationship between HERF and RTAN would indicate that ITS is associated with few major innovators. A statistically significant relationship between ENTRY and RTAN would indicate that ITS is guided by the arrival of new innovators. At the same time, a positive relationship between the combination of HERF and ENTRY and RTAN would indicate that countries could benefit from the presence of both a core of stable and persistent innovators and a pool of new innovators.

c) COPATF_{it}: the amount of co-patenting firms in group i divided by the total number of patenting firms in the same group. A firm is defined a *co-patenting* firm if it has at least one patent application in common with other firms, research centres and universities. It represents the degree of technological co-operation among firms in patenting activity through the propensity to co-patent of firms in a specific technological class and country, and ranges between 0 and 1. This variable clearly covers a small part of the possible collaborations between firms in technologies. Nevertheless, we believe it is worthwhile to ask whether even this small aspect of technological co-operation has statistical significance in its association with ITS.

Finally, we include a specification with a lagged value of the index of ITS: $\mathrm{RTAN}_{i,t-1}$. Previous empirical analyses indicate that ITS displays a high degree of persistency over time. $\mathrm{RTAN}_{i,t-1}$ is used to estimate the level of past-dependency due to historical and firm specific factors that cannot be accounted for by the other variables included in our specification. Persistency in ITS is due to the development by firms of specific technological competitive and advantages, which have been built over time, and to first mover advantages and some forms of increasing returns, inertia and path-dependency.

[16] In addition, the Entropy index is often used in the analysis of variety and concentration (e.g. Grupp, 1996; Frenken et al., 1999). The Herfindahl and Entropy indexes have the advantage over other concentration indexes that are not independent from the number of firms. Moreover, they share a common set of properties which makes them the most used concentration indexes (Encaoua and Jacquemin, 1980; Grupp, 1990).

6 Econometric specification and results

Our main specification (1) takes the following form:

$$\mathrm{RTAN}_{i,t} = \alpha_i + \sum_{j=0,1} \beta_j \mathrm{LINCIT}_{i,t-j} + \sum_{j=0,1} \gamma_j \mathrm{COPATF}_{i,t-j} + \sum_{j=0,1} \eta_j \mathrm{ENTRY}_{i,t-j} + \sum_{j=0,1} \lambda_j \mathrm{HERF}_{i,t-j} + \varepsilon_{it} \quad (1)$$

$i = 1, ..., 555$ cross-sectional groups (111 technological classes and 5 countries), t=1, . . . , 3 periods.

We expect that the impact of different market structures on ITS is not simultaneous. Therefore, the RTAN values are affected by contemporary and past values of the independent variables and, in particular, of concentration and entry. However, as emphasised in Section 4, the relationship between ITS and market structure may be endogenous because past values of ITS may enhance the development of top innovators or stimulate entry of new innovators and, accordingly, affect the structure of innovative activities. We address this problem first by including the (one subperiod) lagged values of the regressors. The lagged values of LINCIT and COPATF are not statistically different from zero and are dropped from the specification. ENTRY and HERF display a high degree of inertia over time and multicollinearity is severe. As a result, only the lagged values are included in the specification.[17]

Second, an endogeneity problem occurs if there is an omitted explanatory variable in the error term which is correlated with the observable regressors. Using fixed effects, we can estimate the partial effects of knowledge links, technological collaboration and market structures on ITS with time constant omitted variables that can be correlated with the regressors.

Finally, we add a specification that contains a lagged dependent variable which provides a simple way to account for historical factors. Of course, we expect a positive estimated coefficient, since ITS has some inertia. In addition, this helps in disentangling the issue that historical high levels of ITS in some technological classes i may be conducive to higher concentration of innovative activity or innovative entry. In this case, instrumental variables are used to address the problem of consistency of the estimated coefficients using fixed effects.

Accordingly, we estimate the following specifications:

$$\mathrm{RTAN}_{i,t} = \alpha_i + \beta \mathrm{LINCIT}_{i,t} + \gamma \mathrm{COPATF}_{i,t} + \eta \mathrm{ENTRY}_{i,t-1} + \lambda \mathrm{HERF}_{i,t-1} + \varepsilon_{it} \quad (2)$$

$$\mathrm{RTAN}_{i,t} = \alpha_i + \tau \mathrm{RTAN}_{i,t-1} + \beta \mathrm{LINCIT}_{i,t} + \gamma \mathrm{COPATF}_{i,t} + \eta \mathrm{ENTRY}_{i,t-1} + \lambda \mathrm{HERF}_{i,t-1} + \varepsilon_{it} \quad (3)$$

[17] The correlation matrix between the regressors is shown in Table 4 in the Appendix. Moreover, auxiliary regressions of $\mathrm{HERF}_{i,t}$ on $\mathrm{HERF}_{i,t-1}$ and $\mathrm{ENTRY}_{i,t}$ on $\mathrm{ENTRY}_{i,t-1}$ display estimated coefficients respectively equal to 0.83^{**} and 0.53^{**} and R-squared equal to 0.60 and 0.32. Finally, the inclusion of two lags would consume an excessive number of degrees of freedom and eliminate time series variation in the panel.

Table 2. Estimation of Eqs. (2) and (3). Standard errors in parenthesis

Dep. variable: $RTAN_{i,t}$	(1)	(2)	(2a)	(2b)	(3)	(4)	(5)
	Random effects	GLS fixed effects	GLS fixed effects	GLS fixed effects	Random effects	GLS effects	IV estimator on first differences
$RTAN_{i,t-1}$	–	–	–	–	0.79**	0.85**	0.53**
	–	–	–	–	(0.02)	(0.008)	(0.37)
$LINCIT_{i,t}$	0.49**	0.31**	0.31**	0.30**	0.20**	0.17**	0.28**
	(0.06)	(0.09)	(0.001)	(0.005)	(0.04)	(0.01)	(0.12)
$COPATF_{i,t}$	0.11**	0.14**	0.14**	0.13**	0.07*	0.06**	0.15**
	(0.04)	(0.05)	(0.002)	(0.003)	(0.04)	(0.01)	(0.06)
$HERF_{i,t-1}$	0.09	0.24**	0.19**	0.32**	0.12**	0.07**	0.45**
	(0.06)	(0.08)	(0.003)	(0.013)	(0.04)	(0.01)	(0.18)
$ENTRY_{i,t-1}$	−0.04	0.06**	0.04**	0.003	−0.04	−0.02	0.05
	(0.04)	(0.002)	(0.001)	(0.016)	(0.03)	(0.01)	(0.05)
$HERF^{*}_{i,t-1}ENTRY_{i,t-1}$			0.07**	0.19**			
			(0.01)	(0.01)			
$ENTRY^{*}_{i,t-1}ENTRY_{i,t-1}$				0.02*			
				(0.01)			
$HERF^{*}_{i,t-1}HERF_{i,t-1}$				−0.27**			
				(0.01)			
R-sq	0.11				0.71		
Wald	81.8**	7740.2**	$5*10^{6}$**	90064**	1913.7**	17430**	
$F_{(5,496)}$							3.75**
$F\_lag1_{(4,496)}$							4.50**
n. obs	1004	1004	1004	1004	1004	1004	502

Our specification is tested against two hypotheses:[18]

(i) that revealed technological advantages are randomly distributed across countries and sectors (see Wald test in Table 2),

(ii) that revealed technological advantages depend only upon their values in the previous period (see F_lag1 in Table 2).

The Hausman test rejects the null hypothesis that the individual effects α_i are uncorrelated with the other regressors ($X^2_{(4)} = 42.18$); therefore, we use a fixed effects approach. However, results from a fixed effect specification still display heteroskedasticity across panels. A fixed effect GLS is thus performed.[19]

The specification proposed seems to catch important aspects of the relation between ITS, knowledge flows and the structure of innovative activities. The hypothesis that RTAN is purely random across countries and across technological classes is rejected at the 99% level of significativity ($\text{Wald}_{(4)} = 7740.2^{**}$ in Table 2).

(i) *Knowledge links within-countries*. Table 2 shows that, consistent with our expectations, ITS is positively associated with our knowledge link variable. The high positive value of the estimated coefficients of the intensity of knowledge linkages with other technological classes in which countries have advantages (LINCIT_{it}) is particularly noteworthy. The positive signs indicate that higher knowledge connections (in terms of patent citations) with technological classes with high specialisation are associated with higher technological advantages in the citing class. This also indicates that strong knowledge linkages with non-specialised technological classes have a negative effect on ITS.

(ii) *Structure of innovative activities*. With regard to the structure of innovative activity, technological advantages are positively associated with the lagged value of the index of innovative concentration ($\text{HERF}_{i,t-1}$). Countries appear to be specialised in technological classes where the oligopolistic core of firms generates the large majority of innovations (in terms of patents). Moreover, in a weaker form, there seems to be a positive association between $\text{RTAN}_{i,t}$ and $\text{ENTRY}_{i,t-1}$. The estimated coefficient in column (2) has a positive sign and is significantly different from zero at the 99% significance level. The positive relation between $\text{ENTRY}_{i,t-1}$ and technological specialisation 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 relation between concentration and technological advantages might not be independent of the rate of entry of innovative firms. In particular, it

[18] The panel is balanced and we have dropped the observational units with missing values. Estimation is performed of a sample of 502 units for two time periods.

[19] There are no noticeable differences between fixed effects and fixed effects GLS estimates and therefore only the latter are displayed in Table 2. Since we use a one-lag version of the model, we have two observations for each individual unit ($T = 2$) and so tests for serial correlation are not available nor necessary (Wooldridge, 2002). We control also for collinearity among the explanatory variables. Correlation matrices (Table 4 in the Appendix A.2) show that there is no severe collinearity between independent variables.

is plausible, as previously discussed, that ITS is affected by a specific combination of concentration and rates of entry. We add an interaction term between concentration and entry $(\text{ENTRY}^*_{i,t-1}\text{HERF}_{i,t-1})$, to test whether the marginal effect of higher innovative concentration on technological advantages increases when entry is higher. The estimated interaction term coefficient does not reject the hypothesis that ITS is affected by a specific combination of concentration and rates of entry. Since the interaction term $\text{ENTRY}^*_{i,t-1}\text{HERF}_{i,t-1}$ is significantly positive, we can claim that the positive relation between the Herfindahl index and $\text{RTAN}_{i,t}$ is higher in the presence of entrants competing with incumbent firms and, alternatively, that the positive relation between the $\text{ENTRY}_{i,t-1}$ and $\text{RTAN}_{i,t}$ turns out to be higher in the presence of higher concentration.

Finally, we test for non linearity in the relation between the Schumpeterian variables and $\text{RTAN}_{i,t}$ including the squared terms for $\text{ENTRY}_{i,t-1}$ and $\text{HERF}_{i,t-1}$. The squared term for $\text{HERF}_{i,t-1}$ is significantly different from zero and negative. This displays the existence of an inverted-U relationship between $\text{RTAN}_{i,t}$ and $\text{HERF}_{i,t-1}$. Both the linear and the squared terms for $\text{HERF}_{i,t-1}$ are statistically significant and they present opposite signs. We suggest, therefore, that ITS is most likely to be associated with a higher level of concentration of innovative activity, but only up to a certain threshold. Thus the probability of observing country c specialised in a technological class j is high for medium levels of $\text{HERF}_{i,t-1}$. Lastly, the impact of the quadratic term $\text{ENTRY}^2_{i,t-1}$ on ITS is significantly positive. Although the size of the coefficient is small, there is evidence of increasing returns to entry of new innovators in terms of revealed technological advantage.

These latter results coupled with the positive estimated value of the interaction coefficient $(\text{ENTRY}^*_{i,t-1}\text{HERF}_{i,t-1})$ seem to confirm the point of Dasgupta and Stiglitz (1980) that there is a positive association between concentration and innovation, provided that the degree of concentration is not too high and that barriers to entry are not too strong. When entry is small, in concentrated industries there may be insufficient incentive to undertake research ventures.

(iii) *Technological co-operation.* 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_{it})), is positively associated with ITS. Even if this index catches only a very limited portion of the many possible forms of collaboration, our evidence suggests that it has a positive impact on the construction of relative technological advantages.

(iv) *Sector specificities.* Finally, the existence of macro-sector specificities indicates that the relationships between the structure of innovative activities and ITS of countries is to some extent sector specific. Results of the estimation of Equation (2) for the three different macro-sectors are displayed in the Appendix (Table 5). The impact of knowledge spillovers on patterns of ITS is particularly strong in Electronics and Machinery. Similarly, technological collaboration affects ITS significantly in all three sectors, but the estimated coefficients are larger in Electronics and Machinery. The estimated effect of innovative concentration on $\text{RTAN}_{i,t}$ is significantly positive in all sectors (particularly in Electronics). The same occurs for $\text{ENTRY}_{i,t-1}$ with one noticeable exception: in Electronics, there is a negative estimated association between innovative entry and ITS.

In Table 2 (cols. 3–5), we display the estimates of Equation 3, which include a lagged dependent variable. Fixed effects estimation cannot be used because of the presence of a lagged dependent variable and a panel with a large cross-sectional dimension coupled with a short time dimension. The short time dimension also creates difficulties in trying to estimate equation 3 using the GMM estimator of Arellano-Bond (1991). We show first the random effects estimates and GLS random effects estimates controlling for heteroskedasticity across panels (cols. 3–4). These coefficients are still inconsistent because of the correlation of the error component and the lagged dependent variable. In order to address this problem, we follow a specification proposed by Anderson and Hsiao (1981), which suggest a first difference transformation of the model and the use of $\text{RTAN}_{i,t-2}$ as an instrument for $(\text{RTAN}_{i,t} - \text{RTAN}_{i,t-1})$. Results are displayed in column 5.

(iv) *Past-dependency*. As expected, the $\text{RTAN}_{i,t-1}$ component is significantly positive and confirms a well-known result on the past-dependency of specialisation patterns. At the same time, the hypothesis that RTAN depends only on its one period lag value is rejected. The knowledge links and the structure of innovative activity variables can be jointly considered statistically significant ($F_{4,496} = 4.50^{**}$).

It is noteworthy that the other estimated coefficients from Equations 3 are not radically different from the ones from Equation 2. Therefore, the results are robust to the inclusion of a lagged dependent variable and only $\text{ENTRY}_{i,t-1}$ becomes not significantly different from zero.

7 Conclusions

This paper studies some factors affecting international technological specialisation (ITS) defined as the international technological performance of a country in a specific technology relative to its overall international technological performance. Recent empirical literature has raised the issue of the plausible explanations of the patterns of ITS. On the one hand, there is widespread evidence that the technological specialisation of countries displays considerable past-dependency and persistency. On the other hand, there is also a high degree of mobility across technological classes.

In our analysis, we used patent applications and patent citations from the European Patent Office for five countries (US, UK, Italy, France, Germany) from 1989 to 1994 for 135 technological classes in three industrial sectors (Chemicals, Electronics and Machinery). We have shown that ITS is significantly persistent and is affected by the direction of cross-sectoral knowledge spillovers within countries. In addition, the concentration of innovative activities, the emergence of new innovators and technological co-operation positively affect ITS.

These results are a first step towards the full inclusion of a group of variables greatly studied in the current literature on innovation and industrial economics – such as knowledge, the structure of competition and the extent of collaboration in a sector – but not used in quantitative analyses of the determinants of the ITS of countries. In particular, this paper underlines the role of knowledge flows across sectors and indicates that knowledge is a key factor affecting specialisation. Our evidence indicates that knowledge spillovers within a country guide and shape patterns of ITS.

In addition, we have shown that both concentration and entry affect positively ITS. Thus specialisation needs the presence of both a core of persistent innovators and a pool of entrants that bring new ideas, new products and new processes into the sector. Our results are in line with the idea of Dasgupta and Stiglitz (1980) that there is a positive association between concentration and innovation provided that the degree of concentration is not too high and that barriers to entry are not too strong. When entry is small, in concentrated industries there may be an insufficient incentive to undertake R&D expenditures.

The relevance of variables related to the structure of innovative activity provides support for enlarging the study of the determinants of technological specialisation to a wider set of variables in the institutional and economic environment. Finally, in line with the sectoral system of innovation approach (Malerba, 2002), we emphasise that the sectoral differences in the relationships between the structure of innovative activities and ITS have to be fully taken into account and require a deeper explanation.

Appendices

A.1 Some examples of the data used

As an example, in Table 3 we show some information that can be drawn from the data set. In the first column, we single out the top three technological classes in which each country is technologically specialised over the period 1991–1992. In the second column, we report the sector to which they belong (C: Chemicals, E: Electronics, M: Machinery). In the third column, we report the normalised technological specialisation indexes: RTAN_{cj}. In column four, we display the top three technological classes, k, which are cited by patents in the classes j in column (1). We exclude the citations that flow within the same technological class and, accordingly, in column (6), $u^k_{cj} = \mathrm{CIT}^k_{cj} / \mathrm{CIT}_{\mathrm{NODIAG}cj}$ is reported. In the last column, the ITS indexes of the cited classes k are presented.

Table 3 shows the manner in which knowledge flows can be represented and assessed using citations. It may be noted, for example, that ITS in the US in Electrical Diagnostic Devices can rely upon knowledge coming from patents developed in the Computer and Equipment technological class in which the US is also specialised. The Computer and Equipment technological class in turn uses knowledge from Telephones, Computer Chips and Radio and Video Equipment.

A knowledge link between specialised classes can be found also in the UK (in Chemicals between Detergents and Insecticides, and between Cosmetics and Insecticides) and in Italy (in the machinery sector).

Table 3. Countries' technological specialisation: top three technological classes with their three most cited classes (period 1991–1992)

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Citing class j	Sector of the citing class j	RTAN of the citing class	Top three cited classes from class j	Sector of the cited class	u^k_{cj}	RTA of the cited class
Germany						
El. shavers. hair-cutting machines, Hoovers	E	0.39	Telephones (no mobile)	E	100%	−0.17
			-None			
			-None			
Wood processing machines	M	0.38	Incecticides	C	40,0%	0
			Spanning machine tools	M	14.5%	0.16
			Saws et al.	M	10.9%	0.20
Printing machines	M	0.37	Conveyors	M	21.6%	0.20
			Photocoping machines and eq.	E	4.7%	−0.3
			Plastic processing	M	2.8%	0.1
France						
Radioactive substances	C	0.60	Catalysts	C	28.5%	0.20
			Carbon acid	C	21.4%	0,00
			Colours. varnishes. pigments	C	21.4%	−0.4
Cosmetics (no soaps)	C	0.42	Other special medicines	C	35.1%	−0.19
			Compounds with nitrogen functions	C	14.5%	−0.17
			Organic and inorganic compounds	C	14.5%	−0.1
Switches. fuses	E	0.42	Control panels	E	53.8%	0.25
			Electro-magnets	E	11.5%	−0.06
			Cables	E	7.2%	0.16
Italy						
Washing machines	E	0.70	Ovens, distilling apparatuses	M	50%	0.13
			Machines for food processing	M	25%	0.50
			Electric heating	E	25%	0.67

Table 3. (continued)

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Citing class j	Sector of the citing class j	RTAN of the citing class	Top three cited classes from class j	Sector of the cited class	u^k_{cj}	RTA of the cited class
Electric heating	E	0.67	Steam boiler	M	66%	0.02
			Ovens, distilling apparatuses	M	17%	0.13
			Agricultural machines (no tractors)	M	17%	0.24
Packaging machines	M	0.62	Conveyors	M	71.4%	0.39
			Saws	M	14.3%	0.23
			Paper production machines	M	14.3%	−0.23
UK						
Organic oils and fat	C	0.7	None	–	–	–
			None	–	–	–
			None	–	–	–
Detergents	C	0.56	Insecticides	C	30.1%	0.19
			Textile machines	M	17.8%	−0.13
			Cosmetics (no soaps)	C	12.3%	0.47
Cosmetics	C	0.47	Insecticides	C	26%	0.19
			Ether, alchool peroxide	C	16.2%	−0.02
			Detergents	C	14.5%	0.56
USA						
Additives	C	0.34	Lubricants et al.	C	17%	0.02
			Carbon acid	C	12.3%	−0.05
			Cosmetics	C	11.5%	−0.01
Electrical diagnostics devices	E	0.33	X-rays	E	29.7%	0.28
			Computers and eq.	E	14.5%	0.28
			Oth. pharmaceutical products	C	14.5%	0.27
Computers and eq.	E	0.28	Telephones	E	40.7%	0.02
			Computer chips	E	15%	−0.13
			TV, radio, video eq.	E	9.1%	−0.05

C: Chemicals, E: Electronics, M: Machinery

$u^k_{cj} = \mathrm{CIT}^k_{cj} / \mathrm{CIT}_{\mathrm{NODIAG}cj}$

A.2. Correlation matrices between the independent variables

Table 4. Correlation coefficients of independent variables , p-values and number of observations

	$LINCIT_{i,t}$	$COPATF_{i,t}$	$HERF_{i,t}$	$HERF_{i,t-1}$	$ENTRY_{i,t}$
$COPATF_{i,t}$	0.009				
	0,76				
	1004				
$HERF_{i,t}$	−0.051	0.156*			
	0.1	0.00			
	1004	1004			
$HERF_{i,t-1}$	−0.077	0.196*	0.776*		
	0.04	0.00	0.00		
	1004	1004	1004		
$ENTRY_{i,t}$	0,508	−0.150*	0.094*	0.063	
	0.03	0.00	0.003	0.047	
	1000	1000	1000	1000	
$ENTRY_{i,t-1}$	0.082*	−0.203*	0.104*	0.073	0.564*
	0.009	0.00	0.001	0.02	0.00
	1004	1004	1004	1004	1000

A.3. Estimated coefficients for three different sectoral sub-samples

Table 5. Estimation of eq. (2) for three different sectoral sub-samples. Standard errors in parenthesis

Dep. variable: $RTAN_{i,t}$	Chemicals	Electronics	Machinery
	GLS fixed effects	GLS fixed effects	GLS fixed effects
$LINCIT_{i,t}$	−0.02	0.44**	0.24**
	(0.01)	(0.022)	(0.02)
$COPATF_{i,t}$	0.07**	0.17**	0.29**
	(0.006)	(0.02)	(0.008)
$HERF_{i,t-1}$	0.13**	0.34**	0.18**
	(0.01)	(0.003)	(0.013)
$ENTRY_{i,t-1}$	0.14**	−0.12**	0.015**
	(0.001)	(0.012)	(0.015)
Wald	$2*10^5$**	2483.2**	3497.7**
n. obs	346	328	330

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