School of Economics and Management
TECHNICAL UNIVERSITY OF LISBON

Department of Economics

Roberto Fontana, Alessandro Nuvolari, Hiroshi Shimitzu, Andrea Vezzulli

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SCHUMPETERIAN PATTERNS OF INNOVATION AND THE SOURCES OF BREAKTHROUGH INVENTIONS: EVIDENCE FROM A DATA-SET OF R&D AWARDS

Roberto Fontana♦, Alessandro Nuvolari♥, Hiroshi Shimitzu♠, Andrea Vezzulli♣

ABSTRACT

This paper examines the relationship between Schumpeterian patterns of innovation and the generation of breakthrough inventions. Our data source for breakthrough inventions is the "R&D 100 awards" competition organized each year by the magazine *Research & Development.* Since 1963, this magazine has been awarding this prize to 100 most technologically significant new products available for sale or licensing in the year preceding the judgment. We use instead USPTO patent data to measure the relevant dimensions of the technological regimes prevailing in each sector and, on this basis of this information, we provide a characterization of each sector in terms of the Schumpeter Mark I/Schumpeter Mark II archetypes. Our main finding is that breakthrough inventions are more likely to emerge in "turbulent" Schumpeter Mark I type of contexts.

♦University of Pavia & KITeS – Bocconi University, Via Sarfatti 25, 20139, Milano, Italy. roberto.fontana@unibocconi.it

♥ LEM – Sant'Anna School of Advanced Studies, Piazza Martiri della Liberta' 33, 56172, Pisa, Italy. alessandro.nuvolari@sssup.it

♠ Institute of Innovation Research – Hitotsubashi University, Tokyo, Japan. shimitzu@iir.hit-u.ac.jp

♣ UECE-ISEG, Universitade Técnica de Lisboa, Rua Miguel Lupi, 20 – 1249-078 Lisboa, Portugal. andreav@iseg.utl.pt

1. INTRODUCTION

One of the "strongest" findings emerging from the rich body of empirical research on innovation carried out over the last thirty years is that innovative activities differ across sectors along many important dimensions such as the knowledge bases underlying innovation processes, the type of actors and institutions involved in innovative activities, the characteristics and the economic effects of innovations (see Malerba, 2005 for an overview). These differences have been highlighted both by detailed case studies of individual sectors (see, for example, the essays collected in Mowery and Nelson, 1999 and Malerba, 2004) and by empirical contributions that have systematically compared quantitative measures innovation with other economic characteristics of sectors (see Cohen, 2010 for a recent overview).

In the evolutionary literature, these differences in the broad patterns of innovative activities across sectors have been highlighted by means of taxonomic exercises. The original aim of these exercises was to identify in the welter of the empirical evidence some archetypical configurations able to capture the key-dimensions in which the structure of innovative activities differs systematically across sectors. Within this approach, one of the most common distinction proposed to describe in a compact way the inter-sectoral differences in patterns of innovation is the characterization of industries in terms of the Schumpeter Mark I and Schumpeter Mark II patterns. Schumpeter Mark I industries are characterized by turbulent environments with relatively low entry barriers where innovations are (mostly) generated and developed by new "entrepreneurial" firms. Accordingly, technological competition among firms in Schumpeter Mark I industries assumes the form of "creative destruction" with successful innovating entrants replacing the incumbents. Vice versa, Schumpeter Mark II industries are characterized by stable environments with relatively high entry barriers in which innovations are generated and developed by large established firms. In Schumpeter Mark II industries technological competition assumes the form of "creative accumulation" with incumbent firms introducing innovations by means of a process of progressive consolidation of their technological capabilities along well established technological trajectories (Malerba, 2005, p. 382). The terms Schumpeter Mark I and Mark II refer to the well-known distinction between the early view of innovation that Schumpeter advanced in *The Theory of Economic Development* (1911) ("Schumpeter Mark I") and the later view proposed by Schumpeter in *Capitalism, Socialism and Democracy* ("Schumpeter Mark II").

A substantial empirical literature has been able to verify the existence of these two patterns of innovation as characteristic of many industrial sectors in different countries using data such as patents (Malerba and Orsenigo, 1995, 1996) or responses to innovation surveys (Castellacci, 2007). Notably, one relatively robust empirical finding is that Schumpeterian patterns of innovation seem to be, by and large, technology-specific. More specifically, in different countries, the same industries tend to display similar patterns of innovation (Malerba and Orsenigo, 1996). Following this cue, most research efforts have been focused on relating the distinction between the two Schumpeterian patterns to a number of specific technological dimensions summarized by the concept of technological regime. A technological regime, as defined by Malerba and Orsenigo (1995, 1996; 1997; Breschi, Malerba and Orsenigo, 2000) is a synthetic description of the "framework conditions" (Castellacci, 2007, p. 1111) in which innovative activities take place. The idea is that these "framework conditions" exert a profound influence on the processes of variety generation and selection among the firms in the sector and through this channel they shape both the organization of innovative activities and the market structure of the industry. Malerba and Orsenigo (1996; 1997) have proposed that the relevant dimensions of a technological regime are the level of technological opportunities, the degree of appropriability of innovations, the cumulativeness of technological advances and the characteristics of the knowledge base underlying innovative activities. In general, the empirical evidence suggests that Schumpeter Mark I patterns of innovation tend to emerge when there are conditions of high technological opportunities, low appropriability and low cumulativeness. Instead, configurations of high appropriability and high cumulativeness are likely to favour the emergence of Schumpeter Mark II pattern.[1]

While most of the contributions in this field have studied the precise relationships between the different dimensions of technological regimes and the sectoral patterns of innovative activities, the overall connection between technological regimes and the innovation performance of sectors have received much less attention. A notable exception is the recent contribution of Castellacci (2007) investigating the relationship between technological regimes and productivity growth.

In this paper we focus on the relation between sectoral patterns of innovation and a more specific dimension of innovative performance, the generation of breakthrough inventions. This approach is somewhat reminiscent of the debate on the "sources of invention" triggered by the famous book of Jewkes, Sawers and Stillerman (1958) during the 1960s. In that book, on the basis of 70 case studies of breakthrough inventions, Jewkes, Sawers and Stillerman argued that, notwithstanding the emergence and consolidation of corporate research laboratories in the twentieth century, the majority of the most significant inventions of the first half of the twentieth century had been actually generated by individual inventors and small companies. In other words the ultimate source of truly significant inventions was outside the walls of the corporate research and development laboratories.

In this paper, we measure innovative performance in terms of the number of breakthrough inventions generated in a sector. For our purposes, we consider as breakthrough inventions the inventions that have won a competition organized by one of the leading magazines for R&D practitioners. In comparison to other measures of innovative performance that have previously used in this context such as patents or productivity,

[1] Schumpeter Mark II patterns are in principle consistent both with low and high degrees of technological opportunities (Breschi, Malerba and Orsenigo, 2000, p. 395).

this type of indicator seem to represent a more “direct” measure of innovative performance. A similar exercise was carried out by Granstrand and Alange (1995) who looked at the sources of the 100 most important innovations introduced in Sweden in the period 1945-1980. Furthermore, since in this paper we shall follow the common practice to use patent data to measure the relevant dimensions of the technological regimes, it seems useful to have a direct indicator of innovative performance at sectoral level that is not also constructed using patents. The rest of the paper is structured as follows. Section 2 contains a condensed summary of previous research on technological regimes and patterns of innovation. Section 3 introduces the data-set of breakthrough innovations. Section 4 reports the results of our empirical analysis. Section 5 concludes.

2. BACKGROUND LITERATURE

In retrospect, modern research on sectoral patterns of innovation emerged out of a growing feeling of dissatisfaction towards the “mixed” empirical evidence produced by exercises aimed at the direct verification of the so-called “Schumpeterian” hypothesis postulating a positive effect of firm size and market concentration on innovation. Following a suggestion of Nelson and Winter (1982), in a number of articles published during the 1990s, Malerba and Orsenigo (1995,1996, 1997) argued that the inconclusive results of the literature studying the relationship between market structure and rates of innovation were due to a failure to properly acknowledge the existence of the different conditions of technological opportunities and appropriability prevailing in each sector and, relatedly, to recognize that both innovation and market structure ought to be regarded as endogenous variables jointly determined by the nature of the prevailing technological regimes.

Malerba and Orsenigo’s approach to this issue was to examine systematically sectoral patterns of innovation across countries using patent data. In general, they found that it was possible to use the Schumpeter Mark I-Schumpeter Mark II classification to characterize systematically the sectoral patterns of innovative activities in all the major industrialized countries. In particular, Malerba and Orsenigo (1995) examined patterns of innovation in different technology classes using USPTO patents over the period 1969-1986 for four European countries (Germany, France, UK and Italy) while Malerba and Orsenigo (1996) carried out a similar exercise using EPO patents over the period 1978-1991 for six major industrialized countries (USA, Germany, UK, France, Italy and Japan). The dimensions considered by Malerba and Orsenigo (1995, 1996) in their assessment of the patterns of innovation were the following: i) concentration and asymmetries among innovating firms in each sector (measured respectively by the C4 concentration ratio and the Herfindahl index computed using the shares of patents hold by different firms), ii) size of the innovating firms (measured as the total share of patents in the technology class belonging to firms with more than 500 employees), iii) changes over time in the hierarchy of innovators (measured using the Spearman correlation coefficient of the patents owned between the innovating firms in different periods), iv) relevance of the entry

of new innovators (measured as the share of patents of firms applying for the first time in a specific technology class).
Malerba and Orsenigo found that technology classes with low concentration and reduced asymmetries among innovating firms tend also to be characterized by relatively small size of innovating firms, changes in the hierarchy of innovators and considerable innovators' entry, pointing towards a Schumpeter Mark I pattern. Vice versa, technology classes with high concentration and asymmetries among innovating firms are also characterized by a large size of innovators, a relative stability in the hierarchy of innovators and limited entry pointing towards a Schumpeter Mark II pattern. These results were further corroborated by a principal component analysis on the variables mentioned above. In all countries, the principal component analysis produces one dominant factor (explaining in all cases more than 50% of the variance) whose loadings are fully consistent with Schumpeter Mark I/Schumpeter Mark II distinction. The overall conclusion of these investigations of the sectoral patterns of innovative activities was that there are systematic differences across in the patterns of innovation (differences that is possible to characterize in terms of the Schumpeter Mark I and Schumpeter Mark II dichotomy) and similarities across countries in sectoral patterns of innovation for a specific technology (Malerba and Orsenigo, 1997, p. 94).

Malerba and Orsenigo's interpretive hypothesis of this finding is that the existence of different sectoral patterns of innovation is accounted for by different "technological regimes" that shape and constraint innovative processes in different sectors. In Malerba and Orsenigo's definition a technological regime is a synthetic description of the technological environment in which firms are situated. More specifically, a technological regime is a specific combination of some basic characteristics of technologies: opportunity conditions, appropriability conditions, cumulativeness of technical progress, nature of the knowledge base (Malerba and Orsenigo, 1997, p. 94). Malerba and Orsenigo 's hypothesis is that Schumpeter Mark I patterns of innovation emerge in contexts characterized by high technological opportunities, low appropriability and low cumulativeness, whereas Schumpeter Mark II pattern emerge in contexts of high appropriability and cumulativeness (technological opportunities can be both high or low). Breschi, Malerba and Orsenigo (2000) provided a first (successful) test of these hypotheses concerning the relationship between technological regimes and sectoral patterns of innovation using data from the PACE innovation survey to measure the relevant dimensions of the technological regimes and EPO patents to measure sectoral patterns of innovation.

More recent empirical contributions have further confirmed the merits of studying sectoral patterns of innovation using the Schumpeter Mark I/ Schumpeter Mark II distinction.[2] Van Dijk (2000) studied the industrial structure and dynamics in the Dutch manufacturing and found consistent differences in the patterns

[2] Several contributions have however argued that the Schumpeter Mark I –Schumpeter Mark II distinction is too narrow and does not map adequately the large empirical variety of inter-sectoral patterns of innovative activities, proposing more articulated taxonomies of innovation patterns. The most famous example is of course Pavitt's taxonomy (Pavitt, 1984). For a discussion, see Marsili and Verspagen (2000).

of industrial dynamics between Schumpeter Mark I and Schumpeter Mark II industries. Schumpeter Mark I industries were characterized by statistically significant lower levels of market concentration, capital intensity and profitability than Schumpeter Mark II industries. Furthermore, Schumpeter Mark I industries are characterized by higher rates of firms' entry and exit than Schumpeter Mark II industries. The distinction between Schumpeter Mark I and Schumpeter Mark II seems also useful to study patterns of innovation with broad technological fields. For example, Corrocher, Malerba and Montobbio (2007) have been able to detect the existence of Schumpeter Mark I and Schumpeter Mark II patterns of innovation examining patents taken in different sub-segments of ICT applications.

Castellacci (2007) has studied the relationship the relationship between differences sectoral productivity growth and technological regimes in nine European countries (Germany, France, Italy, Netherlands, Norway, Portugal, Sweden, UK and Austria) in the period 1996-2001. Following Malerba and Orsenigo's approach, technological regimes are defined in terms of technological opportunities, appropriability and cumulativeness. The measurement of the different dimensions of technological regimes is based on responses to the CIS surveys. Castellacci finds that Schumpeter Mark II are characterized by higher rates of productivity growth. Furthermore, the relationship between the different characteristics of the technological regimes and productivity is different in the two Schumpeterian patterns.

In this paper we consider another dimension of innovation performance namely, the generation of breakthrough inventions. Historians of technology and economic historians have frequently acknowledged that serendipity plays a large role in the generation of breakthrough inventions. Mokyr (1990, p. 13) is possibly summarizing what is the conventional wisdom on this issue when he writes: "macro-inventions[…] do not seem to obey obvious laws, do not necessarily respond to incentives and defy most attempts to relate them to exogenous economic variables. Many of them resulted from strokes of genius, luck or serendipity. Technological history, therefore, retains an unexplained component that defies explanation in purely economic terms. In other words, luck and inspiration mattered, and thus individuals made a difference". Still, some empirical investigations have found that is actually possible to identify some significant relationship between breakthrough inventions and economic variables (Khan and Sokoloff, 1993).

In this paper we shall not deal directly with the issue of the possible economic and social determinants of major macro-inventions, but we shall limit ourselves to study the possible role played by different Schumpeterian patterns of innovation in the generation of breakthrough inventions. A similar exercise was carried out by Granstrand and Alange (1995) for the Swedish case using a sample of 100 "significant" inventions occurred in the period 1945-1980, although their focus was not so much on the impact of the technological regimes, but on the relative contribution of different organizational structures (individual inventors, small firms, large firms) to the generation of inventive breakthroughs. Their findings were mixed. They found that large firms were responsible for 80% of the inventions in their sample, but still a sizable share of breakthrough inventions (i.e, the remaining 20%) could be ascribed to individual inventors and small firms, somewhat vindicating the intuition of Jewkes, Sawers and Stillerman (1958) that individual inventors and small firms were not becoming obsolete.

3. The "R&D 100" Awards Database

Our source of data is the 'R&D 100 Awards' competition organized by the magazine *Research and Development* (previously called *Industrial Research*). The magazine was founded in 1959 and it represents probably one of the most authoritative regular publications for R&D practitioners. Currently it has an estimated monthly readership of over 80,000. It is estimated that about 75% of the readers work in high-tech industries, whereas the remaining 25% works for government laboratories, universities, and similar organizations. Over 60% of the readers have managerial or executive type of jobs. The 'R&D 100 Awards' competition has been running continuously since 1963. Each year the magazine awards with a prize the 100 most technologically significant products available for sale or licensing in the year preceding the judgment.

Throughout the years, key breakthroughs inventions such as Polacolor film (1963), the flashcube (1965), the automated teller machine (1973), the halogen lamp (1974), the fax machine (1975), the liquid crystal display (1980), the printer (1986), the Kodak Photo CD (1991), the Nicoderm antismoking patch (1992), Taxol anticancer drug (1993), lab on a chip (1996), and HDTV (1998) have received the prize. In order to apply for the prize, the inventors or their companies must fill an application form providing a detailed description of the product in question. The prize is awarded only to those products whose applications have been regularly submitted. The prize consists of a plaque which is presented in a special ceremony. There is no sum of money involved. The prize is awarded by a jury composed of university professors, industrial researchers and consultants with a certified level of competence in the specific areas they are called to asses. The members of the jury are selected by the editor of the magazine. The main criteria for assessment are two: i) technological significance (i.e., whether the product can be considered a major breakthrough from a technical point of view); ii) competitive significance (i.e., how the performance of the product compares to rival solutions available on the market).

The product must exist in marketable form at the moment of the submission of the application. This means that applicants are also required to provide evidence of the existence of the invention in marketable form. Applicants are not restricted to firms, but also governmental laboratories, universities, public research centres can compete. It is possible for organizations to submit a joint application for a specific product (in that case the application should include all the organizations that have given a significant contribution to the creation of the product). Finally an organization may submit as many products as they wish at each yearly competition.

There are a number of characteristics of the R&D 100 awards competition that, at least prima facie, appear particularly promising for using this data source to measure inventive breakthroughs. First, the R&D 100 awards competition seems to represent a good opportunity for companies, government laboratories, *etc.* to showcase the outcome of their inventive activities. Thus, we can expect that the awards will provide us with a fairly reliable sample of inventions attained by R&D performers. Second, R&D 100 awards are granted to inventions that, at least in principle, should embody a significant improvement of the state-of-the-art that is clearly documented. In other words awarded inventions should represent a technological breakthrough. Third, the selection of the awards is made by what appears a competent, authoritative jury of experts. Fourth, R&D awards may be assigned both to patented and not-patented inventions. Finally, there seems to be limited space for strategic behaviors and attempts to conditioning the jury, because the nature of the prize is simply honorific.

Given these properties, it is somewhat surprising that economists of innovation have so far paid just scant attention to this type of data. To the best of our knowledge, the R&D 100 awards data have been used so far only used in two contributions: Carpenter, Narin and Woolf (1981) and Scherer (1989). Carpenter, Narin and Woolf (1981) used the 1969 and 1970 awards list and match these inventions with the corresponding US patents. In this way, they obtain a set of 100 patents whose technological significance has been "certified" by the granting of the award. Then they compare the citations received by this group of patents with the citations received by a random sample of patents distributed with the same time cohort. The results show that the patents covering the R&D 100 awards receive a significantly higher number of citations than the control group. In the interpretation of the authors, the results provide an important corroboration for the use of citation received as indicator of patent quality. Scherer (1989) instead used information on the mean and maximum R&D costs of the awarded invention which for some prizes was provided until the 1980s with the list of the winners. From our perspective, it is reassuring that the two authoritative contributions in the field of innovation studies have made use of the data to study the nature of breakthrough inventions.

4. EMPIRICAL ANALYSIS

Retrieving the information from different issues the magazine, we have constructed a data-set with all the R&D 100 awards granted from 1963 to 2005. In this section we use the "R&D 100" data-set to carry out to study the impact of different Schumpeterian regimes on the generation of breakthrough inventions. In particular we proceed in two steps. First, we provide some preliminary descriptive statistics of the dataset to check the reliability of the source. Second, we carry out an econometric exercise of the determinants of the probability of the occurrence of breakthrough invention as a function of the Schumpeterian regime prevailing at the sectoral level.

4.1. DESCRIPTIVE STATISTICS

Figure 1 displays the share of awards granted to US applicants for the prize. The nationality of the applicants has been assigned using the organization, rather than by looking at the nationality of the inventors. The trend of the figure is quite clear. Over the period 1963-2002, the share of US awards is declining indicating that other countries are closing the gap with the US in terms of technological performance. Interestingly enough, the period 2003-2005 seems to be one where the US are regaining and edge in technological, but, of course, it is a too short span of time for detecting clear trends.

[Insert Figure 1 about here]

Figure 2 displays the share of awards received by applicants from different countries by sub-periods excluding the US that, as one would have expected given the nature of the competition and the place of publication of the magazine, dominate the sample. The figures clearly indicate that Japan and Germany are the two most prominent followers of US technological leadership. Figure 2 shows how this effort of closing the gap evolved over time, with Japan and Germany progressively overtaking two older established players such as France and UK. It is interesting to note that the figures reveal a good performance of some small countries such as Sweden, Finland, the Netherlands and Israel notoriously characterized by "dynamic" and successful national systems of innovation. On the contrary countries with good level of economic performance but characterized by historically weak national innovation systems such as Italy display a poor performance.

[Insert Figure 2 about here]

Figure 3 shows the shares of awards granted to different type of organizations. The trends here are consistent with the literature that has recently pointed out the increasing involvement in inventive activities of a number of new actors such as government laboratories and universities. Whereas in the early 1960s corporations were the primary source of inventions, in the most recent years this is clearly not the case.

[Insert Figure 3 about here]

Figure 4 displays the number of inventions receiving an award that are the outcome of collaborative activities. The figure shows a clear increasing trend which is fully consistent with the emphasis that has been put on the growing role of cooperation and networking in the field of innovative activities (Freeman, 1991).

[Insert Figure 4 about here]

After describing these general features of the data, it is interesting to examine the pattern of breakthrough inventions by content type. The inventions winning the R&D 100 awards are classified by the magazine in a number of different categories. However, the classification is not consistent over time and in some cases the inventions were not even assigned to a specific category. Thus, in order to examine the distribution of awarded inventions across different technological fields, we have proceeded as follows. First we have reclassified each awarded invention according to a technology-oriented classification of 30 different sectors based on the co-occurrence of the International Patent Classification (IPC) codes proposed by the *Observatoire des Sciences et des Techniques* (OST).[3] In a few doubtful cases, we have relied both upon the classification in product categories of the R&D100 awards and on the invention description. It is important to note that we have assigned each awarded inventions to only one of the 30 OST sectors. These sectors have been further aggregated into 5 'macro' technological classes (called 'OST5' henceforth) defined according to the ISI-INIPI-OST patent classification based on the EPO IPC technological classes, as reported in Table 1.[4]

[Insert Table 1 about here]

Figure 5 contains histograms showing the distribution of the awarded inventions across the 30 OST sectors.

[Insert Figure 5 about here]

It is important to note that there is no effort on the part of the jury to make sure that the yearly list of winners would cover a large spectrum of technologies. The only criteria adopted are those mentioned in the previous section, that is to say technological and competitive significance. For this reason Figure 5 provides the best indication of the possible biases of the R&D awards in terms of representation of inventive breakthrough activities. As one would have expected, there is a distortion towards 'high-tech' sectors such as instruments, biotechnology, information and communication technologies, optics (lasers), semiconductors, etc. The predominant technology is the field of instrumentation (control instruments). On the one hand, this may be clearly explained by the interests of the editors and the readership of the magazine given that instrumentation plays a central role in the majority of modern R&D processes. On the other hand, this may be the consequence of the fact that it is easier for inventions in these categories to prove that they are superior to the state of the art, by means of quantitative assessment of technological performance. All in all, these results confirm that the R&D 100 awards tend to cover, as one would have expected, a high-tech R&D intensive segment of the economy.

Finally we check whether the R&D 100 inventions that were patented (more specifically those for which we were able to match with one USPTO patent) receive more citations than an analogous random sample of patents. Accordingly, for each R&D inventions with a USPTO patent we construct a "matched random"

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3 See Hinze, Reiss, and Schmoch (1997)

4 Technology-oriented classification system jointly elaborated by the German Fraunhofer Institute of Systems and Innovation Research (ISI), the French Patent Office (INIPI) and the Observatoire des Science and des Techniques (OST).

sample of ten patents of the same granted year and of the same IPC class. The results of this test are reported in Table 2.[5] The non parametric Mann-Whitney test confirms that the median number of citations of patents associated with a R&D 100 invention is significantly higher than the median of the random matched sample. These results confirm the early findings of Carpenter, Narin and Woolf (1981) obtained for the two years 1969-1970 of awards and provides an important corroboration for our use of the R&D 100 data set to assess the influence of different sectoral patterns of innovation on the generation of breakthrough inventions.

[Insert Table 2 about here]

4.2. SCHUMPETERIAN PATTERNS OF INNOVATION AND BREAKTHROUGH INVENTIONS

In this section we carry out our econometric exercise. The aim is to provide empirical evidence on how different patterns of innovation regimes, as measured by patent indicators, affect the probability to observe an breakthrough invention (i.e. an awarded invention) in a given macro-sector.

Our main explanatory variables are constituted by a set of time-varying indicators constructed using patent based data for each of the five macro-classes mentioned above. These indicators aim at at capturing different patterns of innovative activities across classes and over time.[6] Following the contributions of Breschi *et al.* (2000), Hall *et al.* (2001) and Corrocher *et al.* (2007), we computed the indicators as follows (where j = 1,..,5 for each OST5 sector and t = 1976,…, 2006 is the year of granting of each patent):

1) $PAT_{GROWTH_{jt}} = \frac{pat_{jt} - pat_{jt-1}}{pat_{jt-1}}$

Where pat_{jt} is the total number of patents granted in OST5 class j in year t.

2) $Entry_{jt} = \frac{newpat_{jt}}{pat_{jt}}$

Where $newpat_{jt}$ is the total number of patents granted in OST5 class j in year t by new innovators (i.e. by firms patenting for the first time in class j).

3) $C4_{jt}$ representing the concentration ratio of the top four patenting firms (in terms of number of patents granted in a given year t and class j).

4) $Stability_{jt}$ is the Spearman rank correlation coefficient between hierarchies (in term of number of patents granted) of firms patenting in year t and firms patenting in year $t-1$ in class j.

[5] The random matched sample includes patents and not 5350 because for some specific years in some technology classes was not possible to collect enough patents to create the match.

[6] Our main source of information is the NBER Patent Data Project which collects a very comprehensive set of information on USPTO patents for the 1976-2006 period (e.g. dates of application and grant, inventors and applicant's name, number of claims, technological classes, forward and backward citations, etc.). The reclassification of all USPTO patents according to the 2008 IPC classification system is available on the NBER Patent Data Project website and it has been performed on the basis of the International Patent Classification Eighth Edition available at: http://www.uspto.gov/go/classification/uspc002/us002toipc8.htm. For a comprehensive description of the database see Hall *et al.* (2001).

Following Breschi, et al. (2000), the last three indicators (*Entry*, *C4* and *Stability*) are then synthesized in a unique indicator called $Schump_{jt}$ by means of principal component analysis. $Schump_{jt}$ is the our main variable of interest and represents the prediction obtained using the scoring coefficients of the first component and the standardized values of the original variables.[7] It provides an indication of the type of Schumpeterian pattern of innovation prevailing in a given class *i* in year *t*. High values of $Schump_{jt}$ reflect an innovation pattern similar to a Mark II type regime (i.e., a "deepening" pattern of innovative activities with a concentrated and stable population of innovators). Low values of $Schump_{jt}$ reflect instead an innovation pattern similar to a Mark I type regime (i.e., a "widening" pattern with a large and turbulent population of innovators) (Breschi *et al.,* 2000). Figure 6 depicts the different trend of $Schump_{jt}$ across the OST5 macro sectors within our time window.

[Insert Figure 6 about here]

Two sectors (Electrical Engineering and Chemistry & Pharma) are consistently close to a Schumpeter Mark II type of patterns, two other sectors (Mechanical and Process Engineering) are close to a Schumpeter Mark I type of pattern and one sector (Instruments) displays an intermediate pattern between these two.

5) $Herfsources_{tech_{jt}}$ is an index of the relative variety of knowledge sources across technological classes and it is calculated in a similar way as in Corrocher *et al.* (2007). Let $a_{jht} = \frac{c_{jht}}{c_{jt}}$ be the share of backward citations from patents granted in year *t* and belonging to OST5 class *j* to previous patents in IPC class *h* (defined at 4 digit level), where c_{jht} is the total number of patents belonging to IPC class *h* and cited by patents granted in year *t* and belonging to OST5 class *j* and $c_{jt} = \sum_h c_{jht}$.

Let then $v_{jht} = \frac{p_{jht}}{p_{jt}}$ be the share of patents (for each granting year *t*) in OST5 class *j* belonging to IPC class *h*.

Let $Herf_{tech_{jt}}$ and $Herfcit_{tech_{jt}}$ be the corrected Herfindahl indexes (Hall, 2000) calculated using respectively the shares c_{jht} and v_{jht} and indicating how much each OST5 class *j* and its knowledge sources are concentrated (in term of number of patents granted and number of backward citations made) across different IPC 4 digit sub-classes in a given year *t*. The resulting relative index of concentration of knowledge sources across IPC technological classes is given by the ratio of the previous two indexes:

$$Herfsources_{tech_{jt}} = \frac{Herfcit_{tech_{jt}}}{Herf_{tech_{jt}}} .$$

[7] The extracted principal component accounts for about 70% of the total variance. The correlations between the principal component and our three original indicators *C4, Entry*, and *Stability* are 0.37, -0.67 and 0.64 respectively.

6) $Herfsources_{firm_{jt}} = \dfrac{Herfcit_{firm_{jt}}}{Herffirm_{jt}}$, this is an index of the relative variety of knowledge sources across firms and it is calculated (for each granting year t) in a similar way as $Herfsources_{tech_{jt}}$. Here the Herfindahl index at the numerator is calculated using the shares of backward citations from patents in class j to patents applied by firm z: $b_{jzt} = \dfrac{d_{jzt}}{d_{jt}}$, where djzt is the total number of cited patents from OST5 class j applied by firm z (excluding self citations) and $d_{jt} = \sum_z d_{jzt}$. The Herfindahl index at the denominator measures the degree of concentration across firms in a given class j calculated with respect to the number of patents granted in a given year t.

7) $Selfsources_{jt} = \dfrac{sc_{jt}}{c_{jt}}$ is an index of intensity of internal knowledge sources and it is defined for each OST5 class *j* and granting year *t* as the ratio between the total number of self-citations (i.e. backward citations to patents applied by the same firm z) over the total number of backward citations.

To these indicators we add also additional 'applicant level' variables and further controls. Our final reference period of analysis ranges from 1977 to 2005 with a total of 2802 inventions awarded.[8] Table 3 gives a comprehensive overview of the variables used in the econometric exercise.

[Insert Table 3 about here]

Tables 4 and 5 instead report the main descriptive statistics of the variables used in the analysis as well as the distribution of the awarded inventions across sectors and over time.

[Insert Tables 4 and 5 about here]

In our first model we analyze which factors affect the probability of observing a breakthrough invention in each OST5 sector by considering both industry-level technological regimes and invention specific characteristics. We assume that both individual (i.e. invention-level) and environmental (i.e. sector-level) characteristics affect the probability of observing a breakthrough invention. Even though in our setting this probability does not obviously reflect directly the specific choice made by an individual amongst a fixed set of alternatives maximizing a latent utility function (McFadden 1974), we can assume that the observed

[8] We dropped the first (1976) and last (2005) year of reference to avoid possible inconsistencies when calculating our time-varying industry indexes based on patent data.

distribution of prizes across sectors (as resulting by the yearly decision of the awarding board) would mimic quite closely how 'nature' chooses in which sectors a breakthrough invention is more likely to occur.

We therefore rely on the estimation of a Conditional Multinomial Logit (CML) model with both alternative-varying and individual-varying covariates. In this setting the probability of observing a breakthrough invention *i* in a given macro-sector *j* is defined as:

$$pr_{ij} = \frac{\exp\left(X_{ij}\beta + Z_i\gamma_i\right)}{\sum_{i=1}^{m}\exp\left(X_{ij}\beta + Z_i\gamma_i\right)} \tag{1}$$

Where X_{ij} are a set of alternative-specific and Z_i are a set of case-specific covariates respectively. Table 6 reports the estimated coefficients for the model.

[Insert Table 6 about here]

The marginal effects for individual-specific covariates are computed as follows:

$$\frac{\partial pr_{ij}}{\partial Z_i} = pr_{ij}\left(\gamma_j - \bar{\gamma}_t\right) \tag{2}$$

where $\bar{\gamma}_t$ is a probability weighted average of the estimated coefficients. The marginal effect for a given alternative-specific covariate x_{rik} (i.e. the value of the covariate x_r for individual *i* and alternative *k*) is computed as:

$$\frac{\partial pr_{ij}}{\partial x_{rik}} = \begin{Bmatrix} pr_{ij}\left(1 - pr_{ij}\right)\beta_r \ for \quad j = k \\ -pr_{ij}pr_{ik}\beta_r \quad for \quad j \neq k \end{Bmatrix} \qquad (3).$$

Thus the own-marginal effect (for *j=k*) has the same sign of the estimated coefficient, whereas the cross-marginal effect (for *j≠k*) has the opposite sign.

In Table 7 below we report only individual-specific and own alternative-specific marginal effects. For each alternative they are computed at the average value of each covariate.

[Insert Table 7 about here]

Collaboration (i.e. having a multiple applicant) (MAPPL) decreases the probability to observe a breakthrough invention in the sector of Instruments (-0.073) whereas it increases the probability of observing a breakthrough invention in the sector of Mechanical Engineering (+0.087). Breakthrough inventions with at least one U.S applicant organization are more likely to occur in the Chemistry & Pharma and Process Engineering sectors, whereas are less likely to occur in the Electrical Engineering sector. The presence of at least one governmental applicant decreases the probability to observe a breakthrough in the Chemistry & Pharma and Mechanical Engineering sectors, whereas it increases the probability to observe an invention in the Electrical Engineering sector. Finally a breakthrough invention with at least one academic applicant is less likely to occur in the Process Engineering and Mechanical Engineering sectors, whereas it is more likely to occur in the Instruments sector.

Turning our attention to the impact of alternative-specific covariates we can notice that *SCHUMP* which is our main variable of interest has a negative and significant marginal effect. This result suggests that breakthrough inventions are more likely to occur in sectors characterized by Schumpeter Mark I type of innovation patterns, than in Schumpeter Mark II. This result appears both in Table 6 and Table 7. This finding is of particular interest also because it is likely that our measure of breakthrough invention will be probably biased towards inventions emerging from the corporate R&D segment of the economy.

Interestingly enough, concerning the variety of knowledge source across firms indicator (*HERFSOURCES_FIRM*) we find that the more the amount of relevant knowledge in a sector is concentrated across firms, the less is the probability of observing a breakthrough invention in that sector. At the same time, however, the probability of observing a breakthrough increases with the degree of knowledge 'cumulativeness' in a given sector as captured by the relative degree at which each firm exploits its internal source of knowledge (*SELFSOURCES*).

4.3. ROBUSTNESS CHECKS AND SENSITIVITY ANALYSIS

The CML model estimated in the previous subsection relies on the Independence of Irrelevant Alternatives (IIA) assumption which states that the relative odds between two alternatives considered (e.g. the probability of awarding an invention in the Instruments vs. Electrical Engineering macro-sectors) is not affected by adding another alternative (e.g. by adding another macro-sector not considered in our analysis) or by changing the characteristics of a third alternative (e.g. by splitting in two the Chemistry and Pharmaceutical macro-sectors). Although this assumption seems plausible in our setting, since we have classified *ex-post* the awarded invention in the OST sectors considered with respect to the decision of the awarding board[9], we report in this sub-section (as a "robustness check" exercise) the estimates of an alternative econometric model which relaxes the IIA assumption. The Alternative-Specific Multinomial Probit (ASMNP) regression

[9] As we already mentioned, the R&D 100 awarding board was not faced with a real choice amongst macro-sectors alternatives when deciding which invention deserved the prize (i.e. there were no "fixed" shares of awards reserved for each sector).

model (Drukker and Gates 2006) assumes a multinomial distribution for the error terms ε_{ij} in each j-alternative latent variable equation pr_{ij}^{*} with a user-specified correlation structure Ω:

$$pr_{ij}^{*} = X_{ij}\beta + Z_{i}\gamma_{i} + \varepsilon_{ij} \text{ and} \tag{3}$$

$\underline{\varepsilon}_{j}^{'} = (\varepsilon_{i1},...,\varepsilon_{iJ})$ ~MVN(0,Ω), for j=1,…,J and i=1,…, N.

The simulated maximum likelihood estimator for the ASMNP is computed using the command asmprobit on STATA 11 – SE version which implements the GHK algorithm (Geweke 1989, Hajivassiliou and McFadden 1998, Keane and Wolpin 1994) to approximate the multivariate distribution function. Tables 8 and 9 report respectively the estimated coefficients and marginal effects of the ASMNP model. In most of the cases, the sign, the statistical significance and the magnitude of the estimates are similar with respect to the CML estimates.

[Insert Tables 8 and 9 about here]

Moreover, for those sectors in which the alternative-specific regressors have the most significant estimated impact (Instruments, Chemistry&Pharma, and Mechanical Engineering), Figure 7 shows the degree of sensitivity of the estimated marginal effects with respect to different levels of the alternative specific regressors considered (in Tables 8 and 9 the marginal effects are computed considering the mean value for continuous variables and a discrete change 0-1 for binary variables) in different sectors.

[Insert Figure 7 about here]

Interestingly enough, the estimated impact of the Schumpeterian regime indicator (SCHUMP), although being always negative, shows a different behavior with respect to the sector considered. In the sector Instruments the estimated negative marginal effect tends to become stronger the more the Schumpeterian regime gets closer to a Mark II type, whereas in Mechanical Engineering the negative impact tends to become weaker. For the sector Chemistry and Pharmaceuticals, although on average the estimated marginal effect of SCHUMP is negative, we observe a U-shaped pattern with a rate of change in the simulated probability of getting an invention awarded which decreases (i.e. the estimated negative impact becomes stronger) when moving from an highly "turbulent" Schumpeterian Mark I type to an "intermediate" type and then increases when moving from an "intermediate" type to an highly "stable" Mark II type regime.

A similar non-monotonic pattern is found when considering the effect of HERFSOURCES_FIRM in the Instruments sector. The rate of change in the simulated probability of observing a breakthrough invention in this sector decreases when moving from a low concentrated (in terms of relevant knowledge owned by firms) to an "average" concentrated scenario and then increases when moving to an highly concentrated one. In the other two sectors considered (Chemistry & Pharmaceuticals and Mechanical Engineering) the estimated negative marginal effects monotonically decreases with the degree of concentration. Finally, concerning the estimated positive impact of the relevance of the internal sources of knowledge (SELFSOURCES), we can see that its intensity tends to decrease with the degree of knowledge "cumulativeness" in the Instruments sector whereas the pattern is inverted-U-shaped for the Chemistry & Pharmaceuticals sector and constant for the Mechanical Engineering sector. Overall, these findings appear somewhat consistent with those of Castellacci (2007) on the relationship between productivity growth and sectoral patterns of innovation. Also in that case Castellacci found that the relationship between productivity growth and the dimensions of the technological regime was articulated in a different way in Schumpeter mark I and Schumpeter mark II patterns.

5. CONCLUDING REMARKS

Economists of innovation have been aware for long time that patterns of innovative activities differ across sectors. So far, most research efforts have been devoted to articulate taxonomies that could be fruitfully employed to interpret the variety of sectoral innovation patterns. In this respect, the Schumpeter Mark I/Schumpeter Mark II distinction has been, together with the Pavitt (1984) taxonomy, the interpretative approach that has gained the widest currency. In fact the characterization of sectoral patterns of innovation in terms of the Schumpeter Mark I/ Schumpeter Mark II distinction has consistently emerged in different countries using different type of data to measure innovative activities (e.g., USPTO patents, EPO patents and national Innovation Surveys responses).

In this paper, we have expanded on this line of research by examining the relationship between different sectoral patterns of innovation (characterized in terms of technological regimes and Schumpeter Mark I/ Schumpeter Mark II patterns) and the generation of breakthrough inventions. To address this issue, we have used two different sources of data. We have used USPTO patents to measure the relevant dimensions of the technological regime prevailing in each sector and, on this basis, we have constructed an indicator of the degree in which each sector can be considered close either to a Schumpeter Mark I or Schumpeter Mark II innovation pattern. We have used a new data set of inventions receiving a prestigious "R&D prize" to measure the number of breakthrough inventions generated by each sectors.

Our results indicate that, in general, a Schumpeter Mark I pattern is significantly related with a higher probability of inducing breakthrough inventions. As already mentioned, this result merits particular attention because the source we use to measure breakthrough invention (the "R&D 100" competition) is likely to be biased in favour of breakthrough inventions stemming from the R&D intensive segments of the economy. This finding may perhaps be interpreted as a vindication of the thesis of Jewkes, Sawers and Stillerman

(1958) who, long ago, argued that inventive activities undertaken outside the walls of the research and development facilities of large corporation were continuing to play a fundamental role for the generation of breakthrough inventions.

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Table 1: Aggregation of the 30 ISI-INPI-OST sectors in 5 macro-classes

MacroISI-INIPI-OST	ISI-INIPI-OST	Technological Class
1	1,2,3,4,5	Electrical engineering
2	6,7,8,27	Instruments
3	9,10,11,12,14,15	Chemistry, Pharmaceuticals
4	13,16,17,18,20,24,25	Process engineering
5	19,21,22,23,26,28,29,30	Mechanical engineering

TABLE 2: PATENT CITATIONS RECEIVED BY R&D 100 INVENTIONS AND A RANDOM SAMPLE OF PATENTS (MATCHED BY GRANTED YEAR AND TECHNOLOGY CLASS)

	Number	Mean	Median	Standard deviation	Min	Max
R&D 100 patents	535	12.88037	7	16.17822	0	137
Random Sample	5335	8.483024	4	14.11133	0	329

Note: Mann-Whitney test rejects the Null Hypothesis of equal populations

TABLE 3: DESCRIPTION OF THE VARIABLES

DEPENDENT VARIABLE	DESCRIPTION	TYPE
OST5	Invention-type classification according to OST5 (see Table1)	5 categorie j=1,2,3,4,5
INDEPENDENT VARIABLES		
Sector-level characteristics	**j=category of the invention (OST5); t=year of award**	
PAT_GROWTH_{jt}	Patent growth rate	continuou
$SCHUMP_{jt}$	Schumpeterian pattern of innovative activities index	continuou
$HERFSOURCES\_TECH_{jt}$	Variety of knowledge sources across technological classes index	continuou
$HERFSOURCES\_FIRM_{jt}$	Variety of knowledge sources across firms index	continuou
$SELFSOURCES_{jt}$	Intensity of internal knowledge sources index	continuou
Invention-level characteristics		
MAPPL	= 1 for multiple applicant organizations, = 0 otherwise	dummy
NINV	Number of inventors	count
USA	= 1 if at least one applicant is a U.S. organization, = 0 otherwise	dummy
GOV	= 1 if at least one applicant is a governmental organization, = 0 otherwise	dummy
ACAD	= 1 if at least one applicant is an academic organization, = 0 otherwise	dummy
Other controls		
dum1986_1995	= 1 the invention has been awarded in the 1986-1995 decade, = 0 otherwise	dummy
dum1996_2005	= 1 the invention has been awarded in the 1996-2005 decade, = 0 otherwise	dummy

TABLE 4: DESCRIPTIVE STATISTICS

Variable	Obs	Mean	Std. Dev.	Min	Max
OST5	2802	2.514	1.322	1	5
PAT_GROWTH_{jt}	2802	0.049	0.126	-0.290	0.478
$SCHUMP_{jt}$	2802	0.261	0.733	-1.412	1.602
$HERFSOURCES\_TECH_{jt}$	2802	0.521	0.103	0.273	0.910
$HERFSOURCES\_FIRM_{jt}$	2802	0.841	0.156	0.565	1.382
$SELFSOURCES_{jt}$	2802	0.142	0.048	0.085	0.448
MAPPL	2802	0.256	0.437	0	1
NINV	2802	1.665	0.902	1	5
USA	2802	0.877	0.329	0	1
GOV	2802	0.320	0.467	0	1
ACAD	2802	0.074	0.262	0	1
dum1986_1995	2802	0	0	0	1
dum1996_2005	2802	0.322	0.467	0	1

TABLE 5: DISTRIBUTION OF "R&D 100" AWARDS ACROSS SECTORS

Year	Electrical Eng.		Instruments		Chemistry & Pharma		Process Eng.		Mechanical Eng.		All sectors	
1977	20	(20.2%)	38	(38.38%)	14	(14.14%)	18	(18.18%)	9	(9.09%)	99	(100%)
1978	24	(24.24%)	37	(37.37%)	17	(17.17%)	14	(14.14%)	7	(7.07%)	99	(100%)
1979	33	(32.35%)	32	(31.37%)	18	(17.65%)	12	(11.76%)	7	(6.86%)	102	(100%)
1980	35	(32.11%)	32	(29.36%)	8	(7.34%)	30	(27.52%)	4	(3.67%)	109	(100%)
1981	24	(24.74%)	47	(48.45%)	7	(7.22%)	13	(13.4%)	6	(6.19%)	97	(100%)
1982	25	(25.25%)	40	(40.4%)	7	(7.07%)	17	(17.17%)	10	(10.1%)	99	(100%)
1983	20	(20.2%)	38	(38.38%)	6	(6.06%)	19	(19.19%)	16	(16.16%)	99	(100%)
1984	24	(24.24%)	44	(44.44%)	0	(0%)	21	(21.21%)	10	(10.1%)	99	(100%)
1985	36	(36.36%)	39	(39.39%)	1	(1.01%)	19	(19.19%)	4	(4.04%)	99	(100%)
1986	34	(34.34%)	37	(37.37%)	0	(0%)	23	(23.23%)	5	(5.05%)	99	(100%)
1987	25	(25%)	50	(50%)	0	(0%)	20	(20%)	5	(5%)	100	(100%)
1988	15	(15%)	60	(60%)	0	(0%)	25	(25%)	0	(0%)	100	(100%)
1989	22	(22.22%)	49	(49.49%)	0	(0%)	21	(21.21%)	7	(7.07%)	99	(100%)
1990	23	(23%)	46	(46%)	0	(0%)	25	(25%)	6	(6%)	100	(100%)
1991	22	(22%)	35	(35%)	5	(5%)	30	(30%)	8	(8%)	100	(100%)
1992	21	(21%)	32	(32%)	8	(8%)	24	(24%)	15	(15%)	100	(100%)
1993	29	(29%)	29	(29%)	8	(8%)	22	(22%)	12	(12%)	100	(100%)
1994	26	(26%)	35	(35%)	5	(5%)	22	(22%)	12	(12%)	100	(100%)
1995	18	(17.82%)	29	(28.71%)	6	(5.94%)	27	(26.73%)	21	(20.79%)	101	(100%)
1996	31	(30.69%)	29	(28.71%)	8	(7.92%)	28	(27.72%)	5	(4.95%)	101	(100%)
1997	27	(27%)	26	(26%)	12	(12%)	23	(23%)	12	(12%)	100	(100%)
1998	26	(26%)	33	(33%)	1	(1%)	30	(30%)	10	(10%)	100	(100%)
1999	28	(28%)	32	(32%)	1	(1%)	26	(26%)	13	(13%)	100	(100%)
2000	26	(26%)	29	(29%)	7	(7%)	33	(33%)	5	(5%)	100	(100%)
2001	26	(26%)	35	(35%)	4	(4%)	24	(24%)	11	(11%)	100	(100%)
2002	32	(32%)	26	(26%)	11	(11%)	23	(23%)	8	(8%)	100	(100%)
2003	31	(31%)	40	(40%)	6	(6%)	12	(12%)	11	(11%)	100	(100%)
2004	25	(25%)	28	(28%)	16	(16%)	21	(21%)	10	(10%)	100	(100%)
Total	728	(25.98%)	1,027	(36.65%)	176	(6.28%)	622	(22.2%)	249	(8.89%)	2,802	(100%)

TABLE 6: CONDITIONAL MULTINOMIAL LOGIT REGRESSIONS

VARIABLES	(1) All sectors	(2) Instruments	(3) Chemistry Pharma	(4) Process Eng.	(5) Mechanical Eng.
MAPPL		-0.237*	-0.349	0.0453	0.605***
		(0.130)	(0.242)	(0.138)	(0.174)
NINV		0.0682	0.185**	0.132**	0.0366
		(0.0583)	(0.0910)	(0.0627)	(0.0829)
USA		0.380***	0.918***	0.848***	0.254
		(0.145)	(0.294)	(0.186)	(0.215)
GOV		-0.124	-0.567***	-0.0606	-0.388**
		(0.113)	(0.212)	(0.124)	(0.172)
ACAD		0.486**	0.319	-0.455*	-0.846**
		(0.201)	(0.333)	(0.247)	(0.355)
dum1986_1995		-0.0995	-0.595**	0.196	-0.114
		(0.152)	(0.246)	(0.164)	(0.226)
dum1996_2005		-0.416***	0.340	-0.0359	-0.348
		(0.146)	(0.311)	(0.181)	(0.260)
PAT_GROWTH	0.603				
	(0.509)				
SCHUMP	-0.481***				
	(0.178)				
HERFSOURCES_TECH	-0.676				
	(1.084)				
HERFSOURCES_FIRM	-1.106***				
	(0.325)				
SELFSOURCES	7.326***				
	(2.311)				
Constant		-0.508**	-3.060***	-2.146***	-1.919***
		(0.234)	(0.481)	(0.435)	(0.433)
Observations	14010	14010	14010	14010	14010

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

TABLE 7: CONDITIONAL MULTINOMIAL LOGIT REGRESSIONS - MARGINAL EFFECTS

VARIABLES	(1) Electrical Eng.	(2) Instruments	(3) Chemistry Pharma	(4) Process Eng.	(5) Mechanical Eng.
Pr(OST5=j | 1 selected)	0.264	0.372	0.056	0.221	0.087
MAPPL	0.008	-0.073***	-0.017	0.017	0.065***
	(0.021)	(0.023)	(0.010)	(0.020)	(0.016)
NINV	-0.018*	0.001	0.007	0.014	-0.003
	(0.010)	(0.011)	(0.004)	(0.009)	(0.006)
USA	-0.110***	0.006	0.025**	0.089***	-0.010
	(0.029)	(0.029)	(0.010)	(0.022)	(0.017)
GOV	0.033*	-0.001	-0.023**	0.014	-0.022*
	(0.020)	(0.022)	(0.009)	(0.018)	(0.011)
ACAD	-0.026	0.167***	0.013	-0.098***	-0.057***
	(0.034)	(0.039)	(0.019)	(0.024)	(0.012)
dum1986_1995	0.009	-0.025	-0.029***	0.052**	-0.007
	(0.026)	(0.027)	(0.010)	(0.022)	(0.017)
dum1996_2005	0.045	-0.089***	0.031*	0.029	-0.015
	(0.028)	(0.027)	(0.018)	(0.026)	(0.017)
PAT_GROWTH	0.117	0.141	0.032	0.104	0.048
	(0.099)	(0.119)	(0.027)	(0.088)	(0.041)
SCHUMP	-0.093***	-0.112***	-0.025***	-0.083***	-0.038***
	(0.035)	(0.042)	(0.010)	(0.031)	(0.014)
HERFSOURCES_TECH	-0.131	-0.158	-0.036	-0.116	-0.054
	(0.210)	(0.253)	(0.057)	(0.533)	(0.086)
HERFSOURCES_FIRM	-0.215***	-0.258***	-0.059***	-0.190***	-0.088***
	(0.063)	(0.076)	(0.001)	(0.056)	(0.026)
SELFSOURCES	1.423***	1.712***	0.388***	1.261***	0.582***
	(0.449)	(0.541)	(0.125)	(0.399)	(0.187)
Observations	14010	14010	14010	14010	14010

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

TABLE 8: ALTERNATIVE SPECIFIC MULTINOMIAL PROBIT REGRESSION

VARIABLES	(1) All sectors	(2) Instruments	(3) Chemistry Pharma	(4) Process Eng.	(5) Mechanical Eng.
MAPPL		-0.134***	-0.142***	0.871	-0.0289
		(0.0375)	(0.0368)	(1.231)	(0.0271)
NINV		0.0820***	0.0878***	0.980**	0.0590***
		(0.0183)	(0.0174)	(0.406)	(0.0141)
USA		0.431***	0.468***	5.941	0.329***
		(0.0409)	(0.0395)	(3.730)	(0.0289)
GOV		-0.148***	-0.161***	0.721	-0.131***
		(0.0385)	(0.0362)	(1.004)	(0.0295)
ACAD		0.211	0.206	-6.023**	0.0583
		(0.157)	(0.162)	(2.661)	(0.127)
dum1986_1995		0.0403	0.0669	3.687***	0.0177
		(0.0443)	(0.0422)	(1.152)	(0.0351)
dum1996_2005		-0.133***	-0.0753*	3.857***	-0.145***
		(0.0435)	(0.0416)	(1.177)	(0.0336)
PAT_GROWTH	0.0905***				
	(0.0231)				
SCHUMP	-0.0971***				
	(0.00389)				
HERFSOURCES_TECH	-0.151***				
	(0.0177)				
HERFSOURCES_FIRM	-0.249***				
	(0.00691)				
SELFSOURCES	0.712***				
	(0.0962)				
Constant		0.162***	0.0459	-2.03***	0.171***
		(0.0612)	(0.0656)	(0.1109)	(0.0470)
Observations	14010	14010	14010	14010	14010

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

TABLE 9: ALTERNATIVE SPECIFIC MULTINOMIALPROBIT REGRESSION - MARGINAL EFFECTS (ALTERNATIVE SPECIFIC REGRESSORS)

VARIABLES	(1) Electrical Eng.	(2) Instruments	(3) Chemistry Pharma	(4) Process Eng.	(5) Mechanical Eng.
Pr(OST5=j | 1 selected)	0. 258	0. 378	0.055	0.218	0.086
PAT_GROWTH	0.0015	0.192**	0.123***	0.0005	0.076*
	(0.001)	(0.080)	(0.046)	(0.001)	(0.044)
SCHUMP	-0.0014*	-0.190***	-0.121***	-0.0005	-0.075**
	(0.0008)	(0.041)	(0.027)	(0.001)	(0.030)
HERFSOURCES_TECH	-0.003	-0.355*	-0.227*	-0.001	-0.140
	(0.002)	(0.209)	(0.091)	(0.005)	(0.097)
HERFSOURCES_FIRM	-0.004**	-0.472***	-0.301***	-0.001	-0.186***
	(0.002)	(0.078)	(0.075)	(0.005)	(0.026)
SELFSOURCES	0.011*	1.473***	0.939***	0.004	0.581**
	(0.006)	(0.360)	(0.215)	(0.009)	(0.258)
Observations	14010	14010	14010	14010	14010

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

LIST OF FIGURES

FIGURE 1: SHARE OF "R&D 100"AWARDS RECEIVED BY US APPLICANTS

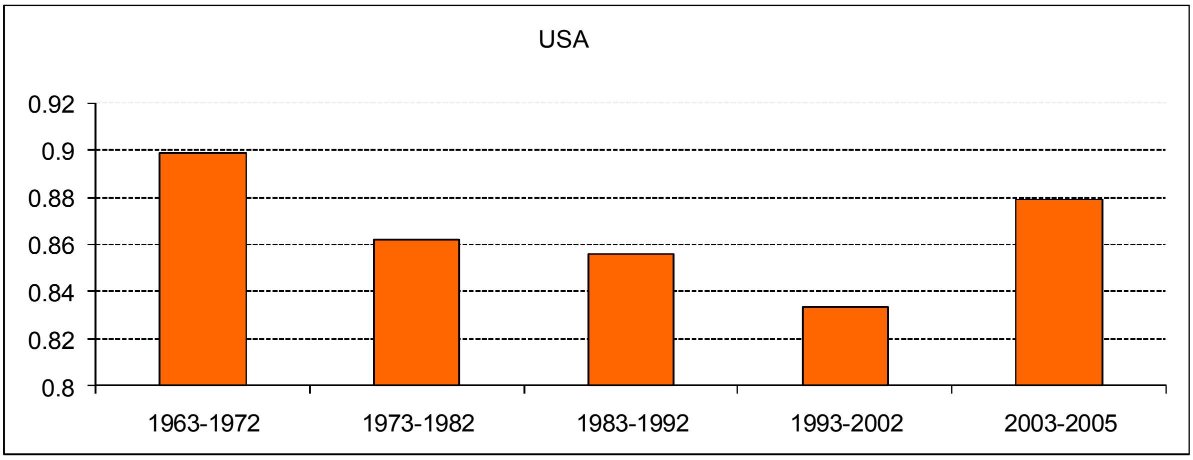

FIGURE 2: SHARE OF "R&D 100" AWARDS RECEIVED BY APPLICANTS OF DIFFERENT COUNTRIES

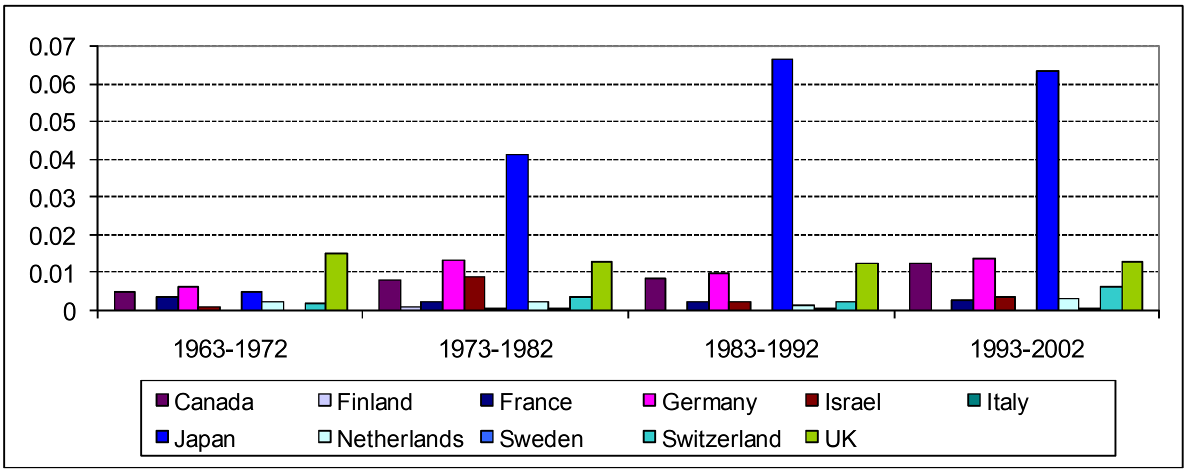

FIGURE 3: SHARES OF "R&D 100" AWARDS GRANTED TO DIFFERENT TYPE OF ORGANIZATION

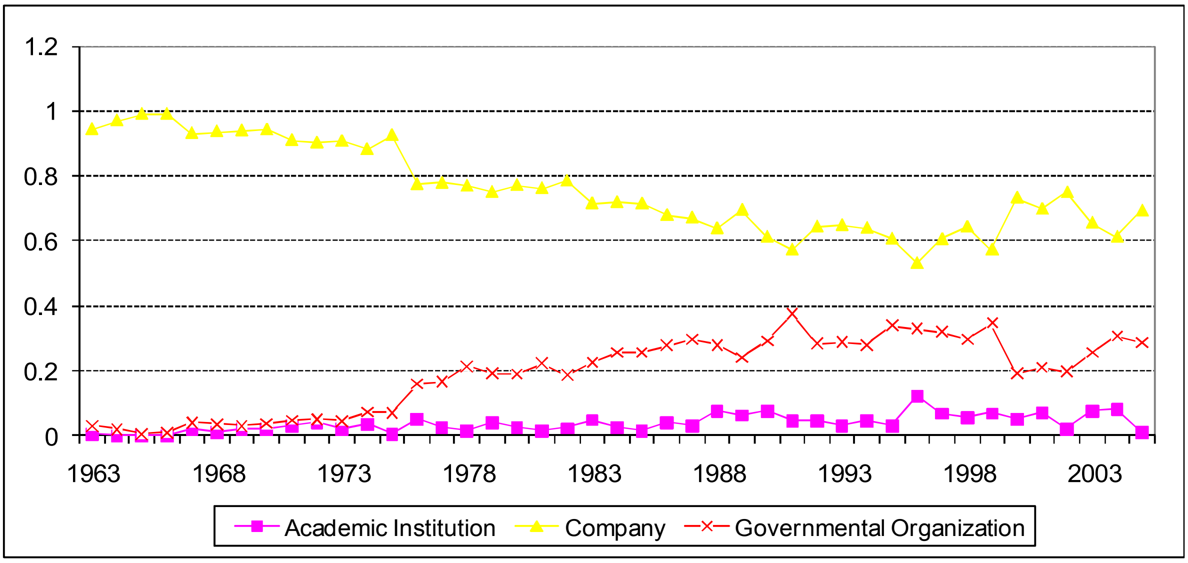

FIGURE 4: NUMBER OF COLLABORATIVE INVENTIONS RECEIVING AN "R&D 100" AWARD

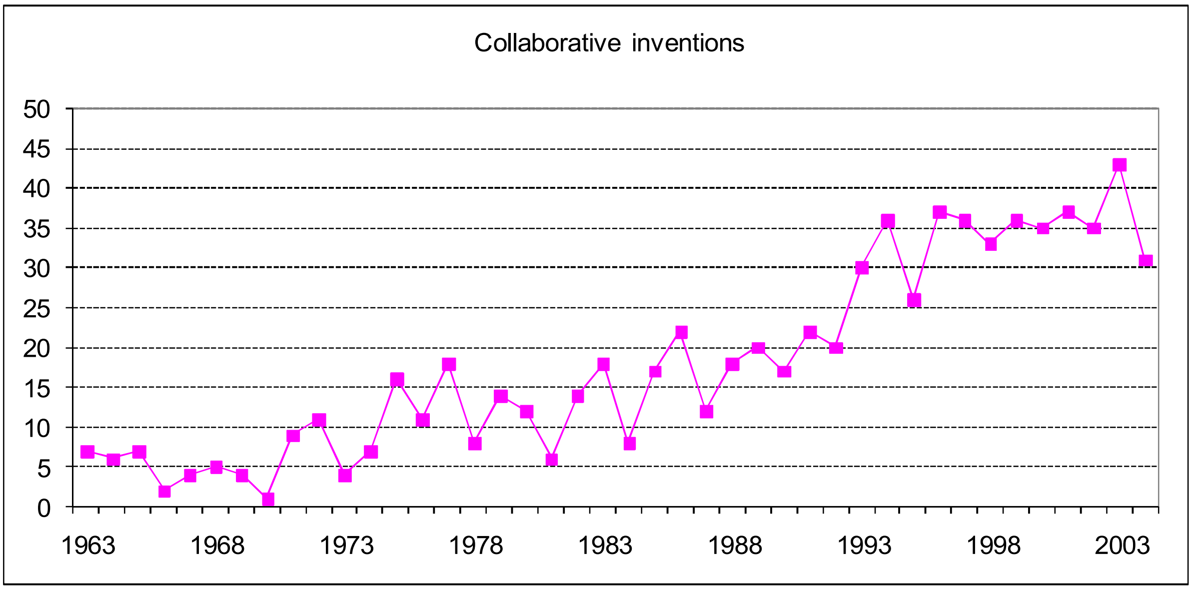

FIGURE 5: DISTRIBUTION OF "R&D 100" AWARDS ACROSS TECHNOLOGY CLASSES, 1963-2005

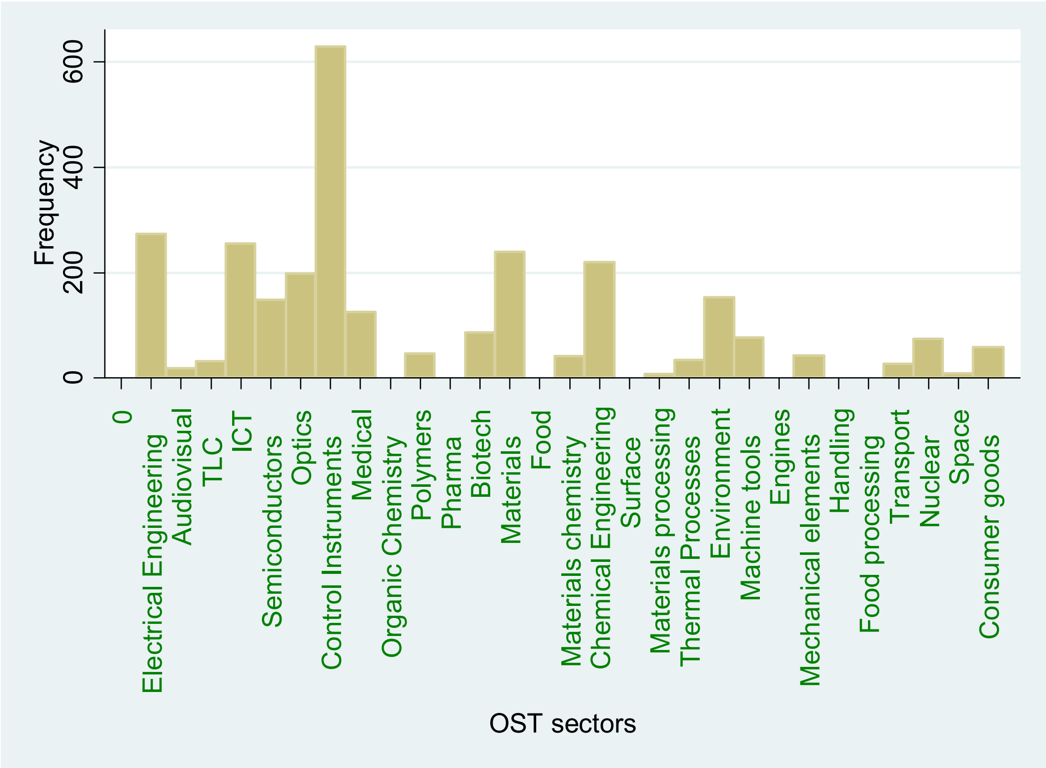

FIGURE 6: THE DYNAMICS OF SCHUMP FOR EACH OST5 MACRO SECTOR (1977-2005)

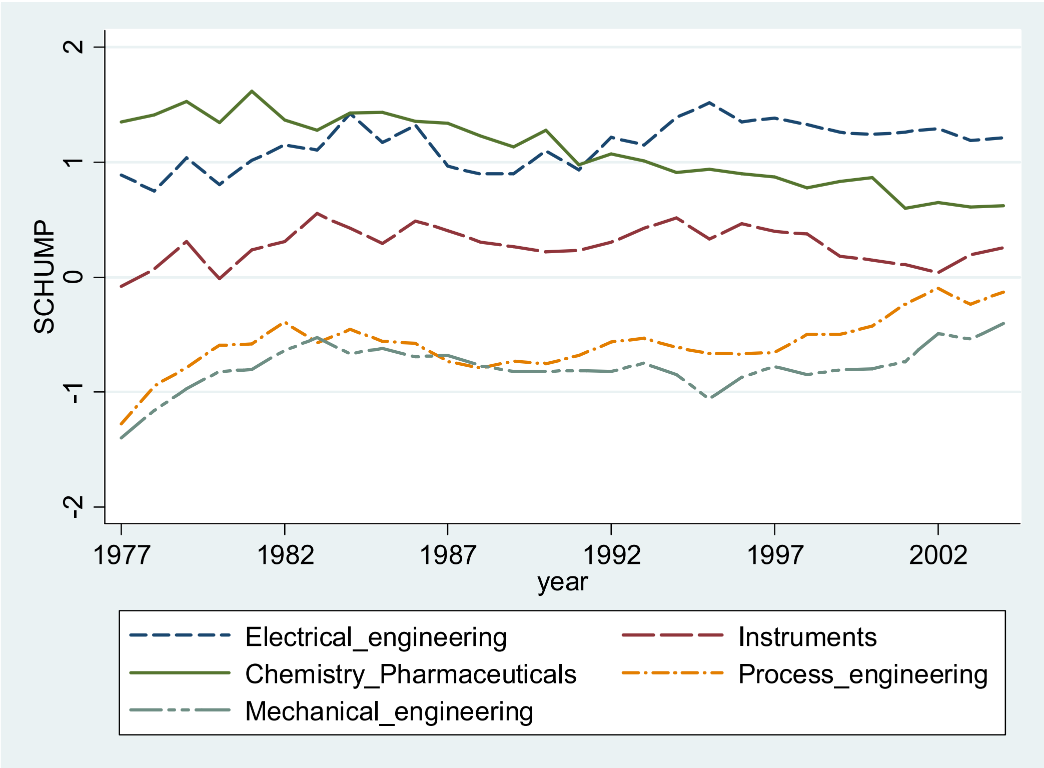

FIGURE 7: ESTIMATED MARGINAL EFFECTS (RED LINE) FOR DIFFERENT VALUES OF THE COVARIATES IN DIFFERENT SECTORS (95% CONFIDENCE INTERVAL IS THE GREY AREA).