FROM PUBLISHING TO PATENTING: HOW TO BECOME AN ACADEMIC INVENTOR?

S. Breschi[1], F. Lissoni[1,2], F. Montobbio[1,3]

[1] Cespri, Università Bocconi, Milan, Italy

[2] Università degli studi di Brescia (corr. author: *lissoni@ing.unibs.it*), Italy

[3] Università degli studi dell'Insubria, Varese Italy

Abstract:
The paper contributes to ongoing debate on the relationship between publishing and patenting in university. By applying event history analysis to patent and publication data for a sample of Italian academic scientists, we show that more productive scientists are more likely to become academic inventors, to no detriment of their orientation towards basic research. Research co-operation with industry is a useful predictor of patenting, when IPRs are owned by business companies.

Keywords: academic inventors; university patenting; open science; scientific productivity

JEL codes: O34; O31; C41

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1. Introduction

The creation and management of intellectual property rights (IPRs) on the results of academic research is nowadays a major policy issue. University patenting has attracted most of the attention, as a result of the impressive growth of patents granted to academic institutions in the US since the approval of the Bayh-Dole Act in 1980, and the related increase of university revenues coming from patent licensing (Mowery et al., 2004; AUTM, 2003). While no other developed country has experienced a similar university patent explosion, the US example has been impressive enough to generate a wave of policy measures in all countries, aimed at increasing university-industry technology transfer and promoting the creation of clear-cut IPRs over the results of public funded research (OECD, 2003).

Evaluating this policy trend requires a better understanding of two distinct issues. First, it is not yet entirely clear whether pushing the faculty to patent the results of their research lead to a genuine increase in the technology transfer efforts, or to a diversion from basic science to more applied targets[1]. In order to shed light on the existence of a possible trade-off between basic research and technology transfer, one needs to investigate the effects of patenting on the academic researchers' core activity, namely the publication of scientific papers on refereed journals.

Second, more information on European countries have to be gathered, in order to avoid that the sheer imitation of the US experience will clash against the institutional specificities of different countries. To date, only the above mentioned OECD report has collected some cross-section data for a few European countries, but they are limited to one year of observation, and to patents owned directly by universities and public labs[2]. For countries such as Germany, where for long IPRs over academic research results were assigned to professors, these statistics may be deceptive. Besides, in the absence of a strong tradition of universities' involvement in IPR matters, it is most likely that researchers receiving at least partial funding from business companies will leave all the IPRs over their research to those companies. Therefore, assessing the contribution of academia to business-owned patents helps evaluating the extent of university-industry transfer links already in place. Finally, longitudinal data are required to evaluate trends.

[1] By "genuine technology transfer effort" we mean here an additional research effort aimed at developing promising inventions already obtained, as "proofs of concept" or "prototypes", by curiosity-driven, or basic research (that is, "normal" academic science). US legislators passing the Bayh-Dole Act aimed precisely at creating the right system of incentives to solicit that effort, under the presumption that a lack of it was undermining the more general goal of promoting innovation by funding science (Jensen and Thursby, 2001). The same presumption seems nowadays to underline the EU policy-makers who believe in the existence of a "European Paradox", that is of a strong European science base, not coupled to effective technology transfer means (Dosi, Llerena and Sylos-Labini, 2005).

[2] Similar data for the case of Finland have been collected by Meyer (2003) and Meyer et al. (2003). For the case of Belgium, see also Saragossi and van Pottelsberghe (2003).

This paper belongs to a series of two aimed at to these two research issues for the Italian case. It is based upon a dataset containing all the patent applications from Italian academic inventors addressed to the European Patent Office, from 1978 to 1999; and on a dataset on publications authored by those academic inventors and a matched sample of academic scientists with no patents in their CV. In particular, we aim at checking whether more productive scientists are more or less prone to patenting, and whether the orientation towards basic research is at odds with or favours patenting. We are also interested in understanding whether the relationship between publishing and patenting varies across disciplines, and between university-owned and business-owned patents; and whether research co-operation with industry is a pre-requisite for patenting.

By applying event history (survival) analysis to our data, we reach the conclusion that more productive scientists are more likely to become academic inventors, to no detriment of their orientation towards basic research. Research co-operation with industry is a useful predictor of patenting only when IPRs are owned by business companies. Environmental factors, such as the presence of other academic inventors in the department, help explaining the propensity to patent.

In section 2 we discuss the existing literature on the academic patenting and its relationship to scientific research and publishing. In section 3 we present our data, while in section 4 we report results of our analysis. Section 5 concludes.

2. Patenting and publishing: complementarities and trade-offs

The relationship between patenting and publishing may be investigated at two different levels, one which refers to the dissemination of research results, the other to the research objectives pursued by scientists.

At the *dissemination* level, one has to explore whether scientific papers and patents are complementary or alternative means for the diffusion of research results. Publishing in peer-reviewed journals has been for long the chief dissemination channels of scientific research results. Well before publication counts started being used as measures of scientific productivity, both for policy evaluation and recruitment purposes, scientists circulated their writings both to diffuse their theories and discoveries, and get credit for them (Chartier, 2003). The history of patents is no shorter, and it is at least since the XVII century that obtaining a patent over a new technology required disclosing the latter's details (MacLeod, 2002). However, it has been argued that patents are nowadays the results of an incentive system at odds with the priority reward system which has governed the scientific community since the XVIII century, as described by Merton (1973). Even if both systems put a prize on keeping research results secret for a while (until the submission of a scientific paper to a journal or conference, or the application for a patent), they have very different disclosure rules and attitudes towards cooperation. The priority reward system encourages scientists to disclose fully their research achievements, *via* the publication of data, intense codification efforts (neat theorizing and establishment of clear experimental routines), teaching duties, and repeated interaction/discussion with peers (Dasgupta and David, 1994). The IPR-based system, on the contrary, may encourage incomplete and selective disclosure. Patent-intensive firms rely heavily on secrecy to appropriate the returns from non-patentable knowledge assets, many of which are produced or acquired along the development phase of a patented invention (Cohen et al., 2000). As long as secrecy complements patenting, academic scientists who are more committed to patent-oriented research may find it difficult to publish all of their research results[3].

At a more practical level, commitment to patenting may push academic inventors to delay the publication of their research results, since placing them in the public domain before filing for a patent would go against the novelty requirement as defined by most patent offices[4].

Both the reduced propensity to publish and the publication delay effects may be stronger for patents resulting from industry-sponsored research, especially when the scientists give away the IPRs over his research to the sponsor as part of research contract[5].

At the *research objectives* level, propositions on the relationship between publishing and patenting derive from more fundamental visions of the relationship between science and technology.

A common concern regards the contents of academic enquiry, which could be diverted from "basic" towards "applied" research. While the former can be portrayed as the unconstrained exploration of nature and theory, the latter's objectives are limited by the need to achieve results with some degree of the "industrial applicability", a crucial pre-requisite for patent applications to be successful. Lack of commitment toward basic research may result either in a lower rate of publications in refereed academic journals, or in less ambitious publications, with a lower impact on the progress of both science and technology. Although never modelled theoretically, the possible existence of a basic-applied science trade-off has been a long standing concern of both policy-makers and scientists (Bok, 2003).

[3] More threats to the overall quantity and quality of scientific publications comes from the increasing cost of accessing research tools (Heller and Eisenberg, 1998), or the scientists' bias when testing products and technologies owned by their business sponsors (as in clinical tests; Campbell et al., 2002).

[4] In principle, the publication delay may be mitigated by the so-called "grace period" rule, as in the US and Japan. The rule allows academic researchers to publish in advance their soon-to-be-patented inventions, as long as the publication occurs not too early (6 to 12 months before the patent application date). However, the European Patent Office does not allow for any grace period, so that any firm or inventor applying for a US or Japanese patent, but foreseeing to extend it to Europe, cannot exploit the rule (Kneller, 2001).

[5] An additional issue relates to patenting of so-called research tools, such as scientific instruments, genetic sequences, and other seminal results. Exclusive licensing and fragmented IPR property over these kind of inventions may prevent research teams with lesser means from accessing to new research fields, or scare off scientists with fears of infringing some hidden patent. On this point, see the classic paper by Heller and Eisenberg (1998), and the more recent empirical work by Murray and Stern (2005) and Sampat (2005).

Alternatively, it has been proposed that close contacts between academic scientists and industry may indeed be beneficial to basic research. The history of science-technology relationships is punctuated by close contacts between scientists and industry, which have provided scientists with financial resources and free access to expensive scientific instruments, as well as with "focussed" research questions, data, and technical expertise. Answers to research questions raised by technology may be at the same time economically valuable and scientifically relevant, up to the point of opening up new research avenues and disciplines: as far as an academic scientist's patenting record is a good proxy of the scientist's involvement with industry at such an high level (rather than mere consultancy) we should expect a positive association between patents and publications (both in quantity and quality)[6].

One further argument suggests that R&D-oriented business companies, especially those active in science-based technologies, are as responsive as academic institutions to scientists' publications. Their R&D staff screen academic publications routinely, publish actively, and participate to conferences and workshops, thus joining the academic community, and sharing its judgements on individual scientists' reputation (Hicks and Katz, 1996; for a survey: Iversen and Kaloudis,1999). It follows that any academic scientists wishing to access the financial and cognitive resources of large business companies must not give up its publication activity, but on the contrary must keep it up at high levels even before producing a patentable invention

Under this perspective, we may expect more productive scientists to exhibit both a strong publication record and a high propensity to appear as inventors on patent documents (whether or not they retain the IPRs over their inventions). At the same time, collaboration with industry may enhance a scientist's productivity.

In a companion paper, we explore the effects of patenting on academic scientists' subsequent publication record (Breschi et al., 2005). Here we do the opposite exercise, and check whether a scientist's publication record may explain her propensity to patent, that is to turn her into an "academic inventor". In particular, we test whether more productive scientists are more or less prone to patenting, and whether the orientation towards basic research bears any relationship with patenting.

We test for the influence of previous collaboration with industry, by including among the determinants of propensity to patent the number of a scientist's papers co-authored with industrial researchers.

We are also interested in understanding whether the relationship between publishing and patenting varies across disciplines, and between university-owned and business-owned patents. We expect the

[6] The classic reference on "cognitive" resources is Rosenberg, 1982, ch. 8. For some recent empirical evidence, see Mansfield (1995, 1998) and Siegel et al. (2003)

probability to observe a positive relationship between publishing and patenting to be higher in scientific fields wherein basic research is more readily exploitable by industry (the classical example being Molecular Biology).

We pursue these research targets by treating patents as discrete events, which may or may not occur at any point in a scientist's career, and may possibly be explained by the scientist's publication record and a number of control variables. By applying a semiparametric survival analysis model, we estimate the impact of each publication-based variable on the patenting hazard rate.

3. Data

The core data of this paper come from the EP-INV database, which contains all patent applications to the European Patent Office (EPO) that designate at least one inventor with an Italian address, from 1978 to early 1999. The EP-INV database contains information on 30243 inventors and 38868 patent applications.

Little more than 1400 of these applications come from 919 "academic inventors", namely university researchers and professors who appear both as designated inventors in the EP-INV dataset and in the complete list of academic staff of science and engineering departments on active duty in year 2000 (27844 full professors, associate professors, or assistant professor) provided to us by MIUR, the Italian Ministry of Education and Research. For a full description of the matching methodology and contents of the dataset, see Balconi et al. (2004).

In this paper we focus on a few disciplines with a very high share of academic inventors over the total number of professors. These can be found in fields such as Chemical Engineering (e.g. technology of materials, such as macromolecular compounds), Biology, Pharmacology, and Electronics (including Telecommunications), for a total of 301 academic inventors and 552 patents (table 1). Many patents are the result of teamwork, with academic and non-academic inventors working together. As for the distribution of patents over time, 75 of them date back to 1979-1985, while the others are quite uniformly distributed over the remaining years. Most of the selected inventors are full professors, born between 1940 and 1960 (more details in Breschi et al., 2005).

{TABLE 1 HERE}

A control sample was then built, by matching each academic inventor to a professor in the same discipline, with the same academic ranking, and of a similar age[7]. Each academic inventor was matched to a colleague never designated as inventors of patents applied for either at EPO or the US Patent and Trademark Office[8]. When possible, controls were chosen among the academic inventors' department colleagues or from university of similar size and importance, or from the same region. We decided not to adopt stricter matching rules at the level of university/department (such as choosing controls only from the same departments of the inventors), as they would have greatly reduced the sample. For the same reason, we did not match our data on the basis of gender. The rules we followed for matching inventors and controls at the university level provide satisfactory results: as far as summary statistics of university size are concerned, we do not find systematic differences between inventors and controls (see table A2 in the Appendix)[9].

3.1 Patent data

The distribution of patents across academic inventors is highly skewed; most professors have signed only one patent, and very few more than five (table 2). Most patents belong to business companies, as a result of contractual funding, with little meaningful differences across fields, with the exception of Biology, which records a higher number of both individual and university-owned patents (table 3). We cannot be sure that all academic inventors signed their patents when they were already working in a university: some patents may be the outcome of former jobs as industrial researchers or employees of large public labs. However, we suspect these patents to be very few, as Italian professors usually start pursuing the academic career right after graduating.

{TABLE 2 HERE}

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[7] The choice of discipline, rank, and age as matching variables follow the best-established results of quantitative studies in the sociology of science (e.g. Long et al., 1993).

[8] For academic inventors born in between 1950 and 1970, we allowed for no more than 5 years of age difference with the controls. For professors born before 1950 the maximum age difference was 7 years. For academic inventors born after 1970 (just one) the maximum age difference reduced to 3 years. Exceptionally (no more than 10 cases) we matched a full professor (inventor) with an associate professor (control), or an associate professor with an assistant professor; in these cases the age criteria were stricter (maximum age difference: 3 and 5 years, respectively).

[9] On how university and department affiliations may affect scientific productivity, see Allison and Long (1987, 1990). The Italian evaluation system of academic activities does not rank systematically universities and departments according

As for IPRs over public-funded research, in principle these belong to the sponsors (most often the MIUR ministry, the National Research Council, and, in the past, ENEA, the National Agency for Alternative Energy). However, until recently, the decision to take the first step towards patenting was usually left to individual grant recipients and, if taken, the step was often met with passive bureaucratic resistance by the funding institutes.

{TABLE 3 HERE}

A similar explanation applies to the scarcity of patents owned by the universities: until recently, universities decided to take care of the application procedure and expenses to reward, often symbolically, some brilliant researcher, rather than as the outcome of a consistent exploitation strategy. As a result, few patent applications from public-funded research are completed, and even less are extended outside the national level (so they do not appear in our dataset). It also happens that many professors take the shortcut of patenting in their own names: this explain the presence of a few inventors' own patents[10]. Finally, some "Open Science" patents come from international collaborations, and are owned or co-owned by US and European universities or consortia.

Table A3 in the Appendix lists the most important applicants as well as the ownership concentration ratios, by field. More than one third of the patents in the Electronics and Telecom field are in the hands of ST Microelectronics, the largest semiconductor company in Italy and one of the very few large hi-tech companies in Italy[11]. As for the other fields, ownership is so sparse that the National Research Council (CNR) and the University of Rome, despite holding very few patents, turn out to be ranked highly among patent applicants.

to the quality of their research. In the absence of better measures, we can measure the university size with the total number of professors (in hard science).

[10] Inventors' own patents, however, are less than suggested by table 3. In fact, whenever an "individual" patent results from teamwork, all co-inventors figure as co-applicants.

[11] In particular, ST Microelectronics has a long cooperation record with, among others, some researchers from the Department of Electronic Engineering of the University of Pavia (Balconi, Borghini and Moisello, 2003). The multinational group ENI plays a similar role in Chemical Engineering, although it has not close relationships with a single university.

It should be noticed that, in a few cases, the CNR and the universities enter table A4 as co-applicants along with business companies, as a result of public-funded co-operative research projects. In this case we assign the patent to the "business" category.

3.2 Institutional and personal data

Most information on individual professors and their institutions come directly from the MIUR list, which contains the professors' date of birth, as well as their discipline, affiliation, and academic ranking (assistant professor, associate professor, and full professor).

Disciplines are defined according to a classification created for administrative purposes; it is very detailed and allows some compression into broader categories, which are referred to as "fields" (see table A1 in the Appendix)[12]. It is hardly common for a professor to change discipline over his career, and when this happens, movements can be safely assume to occur within the same field.

Affiliation refers to the university employing professors in year 2000. For each university we know the size of the scientific faculty ($NUNI_j$: n. of professors in hard sciences in university *j* in year 2000); we expect larger university to be better equipped in dealing with technology transfer issues, as they may have some administrative staff devoted to manage intellectual property rights. We also calculate the weight of the university in a specific field ($USSDW_j$: n. of professors in university *j* / n. of professors in Italy, by field) as well as the weight of the field within the university ($SSDUW_j$: n. of professors in a given field in university *j* / n. of professors in university *j*, for each field): we consider the former as a proxy of the strength or prestige of the professor's department within his own university, and the latter as a proxy of the strength or prestige of the professor's university in the Italian academic system, in the professor's field. Strenght or prestige may influence the availability of research funds, from which the opportunity to invent may follow.

In the absence of longitudinal data on both the professors' affiliation, and the faculty size of universities, we will make use of NUNI, USSDW and SSDUW as control variables throughout our analysis, for all years comprised between 1978 and 1999. We justify this use of our data by pointing out that academic mobility is a very limited phenomenon in Italy, and it is often confined to the very early stages of a professor's career. As for the absolute size of university faculties, this has increased greatly over the years, but the same cannot be said of relative size: public universities in Milan, Rome, and a few other large cities have remained the dominant institutions despite all changes. We

[12] The MIUR list includes only those professors and researchers with tenured position (from now on, we will refer to them simply as "professors"). Thus our data miss fixed-term appointees who, at the time, had been working in one or more universities for one or more years, as well as all the PhD students, post-doc fellows, and technicians. In the current Italian system, assistant professor (called "researcher") and associate professor positions, despite being only the first two steps of the academic career, are not offered as fixed-term appointments, but as tenured ones. The main differences with the position of full professor lie in wage and administrative power.

assume our variables to capture effectively the effects on academic patenting of university size ranking, and to influence positively the propensity of a professor to sign a patent as inventor.

Other control variables we obtain from the MIUR list are the AGE and GENDER of professors (GENDER equals 1 for women professors).

By combining our patent data and information on affiliation (in 2000), we have produced two additional control variables: SHAREINV, which measures the percentage of inventors among each professor's colleagues (in the same university and field), at each point in time; CUMPATUNI, which measures the stock of patents held by each professor's university at each point in time. We expect both of them to influence positively a professor's propensity to sign a patent as inventor.

The main drawback of our data is the absence of information on either the graduation year or the starting date of our professors' careers. This will force us to make some rules-of-thumb assumptions when dealing with the entry date in our longitudinal dataset (see sections 3.3 and section 4 below).

However, for a subset of 139 academic inventors, additional data are available on their graduation year (which allows to set a more precise entry date in our longitudinal dataset) and on whether they hold a PhD, and when it was completed (from which we build a PHD dummy which takes value 1 from the PhD grant year onward). When limiting our analysis to academic inventors we will make use of these more precise pieces of information.

3.3 Publication data

For academic inventors and their controls we collected scientific publications from the 2003 web edition of the ISI Science Citation Index (SCI), starting from articles published in 1975.

For each professor we compute the average number of publications (AVG_PUB) at each point in time, as the stock of publications divided by the years of activity. We expect AVG_PUB to influence positively the academic researchers' propensity to patent, at least in those fields where science leads more directly to invention.

Calculating the number of years of activity requires setting a starting date for a professor's career. In the absence of information on either the graduation year or the first year as assistant professor, we set the starting date as the minimum between the 30th birth-year and the first year of publication activity. This choice will possibly lead to overestimating the publication activity of professors with no papers in the early stages of their career, as those years may be dropped from our analysis. This possibility is most likely to occur for non-inventors, who record a higher number of zero-publication years (see figure 1) and appear in general to be less productive than inventors (table 4). As we will find (section

4) that AVG_PUB indeed is most often positively related to patenting, we conclude that this measurement problem does not undermine our conclusions.

{FIGURE 1 HERE}

{TABLE 4 HERE}

To test for the possibility that patenting occurs as a consequence of an intense research effort, which produces jointly publishable and patentable results, we compute DELTA_PUB as the difference between the yearly scientific production of a professor, and his current AVG_PUB value. We also compute the 1- and 2-lagged values of DELTA_PUB.

Information on a professor's research targets (basic vs. applied) come from a reclassification, produced by CHI Research, of about 90% ISI-recorded journals (Hamilton, 2003). Journals are assigned a score from 1 to 4 on the basis of their contents and scientific field, with score 1 for the most applied kind of research and score 4 for the most basic[13]. We calculate AVG_BASIC and DELTA_BASIC as the equivalents of AVG_PUB and DELTA_PUB for the journals with score 3 and 4.

Finally, in order to assess the extent of pre-existing research co-operation between academic researchers and industry, we have calculated S_COPAT: for each in point in time, it represents the share of cumulated publications co-authored by each professor with industrial researchers affiliated to companies with at least one EPO patent application (not just Italian ones, but worldwide). Information on the affiliation of professors' co-authors come again from ISI-Web of Science, while

[13] The classification distinguishes between biomedical fields and all the other disciplines. In the first case, the scores correspond to the following definitions of the journals' contents:

1 = "clinical observation" (eg. Journal of the American Medical Association)
2 = "clinical observation and investigation" (eg New England J. of Medicine)
3 = "clinical investigation" (eg Journal of Clinical Investigation)
4 = "basic biomedical research" (eg Journal of Biological Chemistry)

In the second case the correspondence is:

1 = "applied technology" (eg Dyes and Pigments)
2 = "engineering science -technological science" (Journal of AOAC International)
3 = "applied research -targeted basic research" (Analytical Chemistry)
4 = "basic scientific research" (J. of the American Chemical Society)

information on worldwide patent applications to EPO come from the K4I dataset on EPO patents (K4I, 2005).

4. Analysis

In order to explore the relationship between publication activity and patenting, we estimate the patenting hazard rate of our subjects, that is the probability that a professor will patent in the current year, conditional upon her not having patented so far (the time unit is the year).

As we do not have any a priori hypothesis on the functional form of the hazard function, we choose to apply Cox semiparametric approach, which does not impose any parametric specification on the baseline hazard function (that is, on the relationship between time and the probability of the event to occur; Kalbfleisch and Prentice, 2002). This means adopting a proportional hazard model such as:

$$h(t_i \mid x_i) = h_0(t_i)\exp(\beta x_i)$$

where $h(t_i|x_i)$ is the hazard rate at time t for professor i, conditional upon a set of covariates x_i, which include both time-invariant characteristics of the professor (such as GENDER) and time-varying ones (such as all variable related to the number of publications).

We first estimate the hazard function for a single patenting event, that is we choose professors as the subjects of our exercise and let them in our sample at the latest between the starting year of their career[14] and 1978 (the opening year of the EPO, European Patent Office); academic inventors exit the sample when they sign their first patent. In other words, we assume professors to be at risk of patenting only from the opening of EPO in 1978, or from when they start their career (if later); and not be anymore at risk once they sign their first patent. Time "at risk" runs from the entry in the sample[15].

{TABLE 5 HERE}

[14] For our definition of "start" of a professor's career see section 3.3 above

[15] This means that we assume no left truncation in our data, as 1978 is the earliest possible entry year for all our professors, no matter whether they started their career before then. In other words, we disregard all patents taken at national offices before the opening of EPO as a relevant event for our analysis (none of our professors signed any US patent before 1978). We justify this treatment of our data by observing that very few professors have more than one patent, so the risk of ignoring some previous patenting activity is low; and that the equivalent of a EPO patent before 1978 should be not just any national patent, but a patent extended to all the most important EPO countries, which makes the risk of ignoring it even smaller.

We then proceed to check whether our results hold for repeated patenting events. In this case, the professors enter our sample first in 1978 (or when they start their career, if later) and never exit, as they are always at risk of patenting; however, after any patent the time "at risk" re-starts from 1, as we assume each patenting event to be distinct from the previous one. Technically, this means assuming that any professor with $n>1$ patents will enter our analysis as $(n+1)$ distinct subjects, each observed from time 1 onward. As we expect the recurrence times of all events concerning the same professor to be highly correlated (that is, they not to be independent observations), we allow for professor-specific random effects (frailty model; Lancaster, 1979). In other words, we assume the hazard function for all m_i observations referred to professor i to be:

$$h(t_{ij} \mid x_{ij}, \alpha_i) = \alpha_i h_0(t_{ij}) \exp(\beta x_{ij}) \qquad \text{with } j=1 \ldots m_i$$

where α_i is a parameter common to all observations. As we do not have any a priori on the probability density function of α_i, we simply adopt the Gamma specification built in STATA, the software package we used for our analysis. Estimates of the hazard function under the assumption of a Gamma-distributed frailty parameter include an estimate of the distribution variance (θ), upon which all standard errors of the parameters for the covariates are conditional. The "frailty" assumption, that is the assumption of random effects at the professor level, is not rejected as long as $\theta \neq 0$.

We finally check our results for a sample limited to the academic inventors only, for a number of which we know both when they started their academic career and whether they hold a PhD.

Table 6 reports our estimates for the coefficients of the single-event hazard function. Equation (1) suggests a positive association between patenting and publishing at two levels: first, professors who experience an above-average publishing activity in year *t-1* are more at risk of patenting the following year; second, more productive professors are more at risk of patenting.

The first relationship derives from the positive and significant coefficient of DELTA_PUB_{t-1}, which implies that the hazard rate increases of about 11% with any additional paper published with the respect to a professor's average. It is hard to assign to this estimate a causal interpretation; rather, it suggests that patenting and publishing are not alternative activities, and that patenting does not impose any significant publication delay to academic inventors.

The second relationship is suggested by the positive value of the AVG-PUB coefficient, which suggests that by adding one paper to a professor's average productivity we obtain a 12% increase of the hazard ratio.

One more relationship between publishing and patenting is the result of a "coauthorship" effects. As suggested by the coefficient of S_COPAT (which ranges from 0 to 1), a 1% increase in the stock of publications co-authored with industrial researchers (whose employers have at least one EPO patent) increases the hazard rate of about 4%. This effect may be stronger than it looks at first sight: publications are count data, and one or two publications more with industrial co-authors may mean much more than a mere 1% increase in S_COPAT (for example, a mere 5% increase in S_COPAT means a 19% increase of the hazard rate).

No age effects are observed, while a limited gender effect is detectable (all other things equal, the hazard ratio for women is 8% less than that of men). As many studies in the sociology of science have pointed out a negative gender effect on scientific productivity, what we have here is an additional gender effect on the probability of patenting: women may be less likely to patent insofar they have a lower publication record (Long at al., 1993), *and* because they are at a disadvantage in patenting the results of their research.

{TABLE 6 HERE}

At the level of institution, the share of academic inventors over the total number of a professor's department colleagues (SHAREINV), exerts some positive effect on the hazard rate, albeit a very limited one (a 50% higher share of academic inventors in the department means only a 1,5% increase of the hazard ratio). No other variable at the institution level is significant.

None of the field dummies appears significant (pharmaceutical is the reference case). This excludes a direct effect of a professor's scientific field on the hazard rate. However, we tested for some indirect effect, by interacting the field dummies with all the publication-related covariates. Neither the interactions with DELTA-PUB nor those with AVG_BASIC appear to be significantly different from each other.

On the contrary, scientific fields affect significantly the impact of S_COPAT on the hazard rate. Equation (2) suggests that the highest effect is recorded in the Pharmaceutical field (baseline coefficient 3.51) , and the lowest in the Chemical field (where the effect appears to be negative: 3.51-8.52=-5.1).

In equation (3) we check whether our results still hold when considering only the publications on journals more oriented to basic science. While the effect of the number of publication at time t-1 ($DELTA\_BASIC_{t-1}$) seems confirmed, the same does not apply to the average number of publications (AVG_BASIC).

{TABLE 7 HERE}

In table 7 we run separate regressions for patents owned by Business companies and patents assigned to Open Science institutions (such as universities or public consortia[16]). As for impact of publications on the hazard rates, no major differences from table 5 stand out, although the effect on the hazard rate of a professor's publications at time t-1 ($DELTA\_PUB_{t-1}$) may be somewhat smaller for the case of Business-owned patents. When only basic science publications are considered no effect of $DELTA\_BASIC_{t-1}$ is visible for Business patents. As for the effect of AVG_BASIC, this does not appear to be significant for Open Science patents. None of these differences, however, appear to be of major importance.

More strikingly (although not surprisingly), coauthorship with industrial researchers seem to affect only the hazard rate for Business patents, with the same sign and possibly higher coefficients than we observed for all patents.

At the same time, the field dummy for Biology appears to be significant for the Open Science patents. This reflects the uneven distribution of patents between the Business and Open Science category, with the latter hosting a larger proportion of patents by Biology professors.

An additional dummy variable (POSTPAT) takes value 1 for all inventors, starting on the year of their first patent. It controls for the possibility that some inventors with Business patents may also patent for an Open Science institution (or vice versa), and that one patenting experience may affect the hazard rate for the other one. Its lag of significance reflect the low number (18) of academic inventors with both kinds of patents.

Finally, we observe that a major difference in the effect of gender, with the disadvantage of women totally confined to Business patents.

In table 8 we check for the robustness of our results by considering multiple events, that is by modelling the hazard rate for both the first patents and the following ones.

[16] We also add to this category the few patents assigned to individual inventors, as they do not originate from ties with industry and are most likely to result from some tacit arrangement between the academic inventor and her university's administration

No major difference appear from the previous table. The loss of significance of the Biology field dummy for the Open Science patents may be explained by the limited number of Biology professors signing more than one patent, so that when counting all events the distribution of patents across fields is less uneven.

As for the loss of significance of $DELTA\_PUB_{t-1}$ for Business Patents, this is due to the fact that multiple Business patents most often appear at a very short time distance (usually at no more than 1 or two years of distance), as they are clearly the result of the same research project; exploration of the data suggest that in these case no further increases of publication activity occurs after the first patent.

The POSTPAT dummy used in table 7 is here replaced by $STOCKPAT_{t-1}$, that is the number of patents signed by the inventor up to t-1. This variable affects only the hazard rate for Open Science patents.

{TABLE 8 HERE}

Finally, table 9 reproduces equation (1) of table 8 only for a subset of 134 academic inventors, whose BA and PhD graduation years we recovered through interviews. The exclusion of the non-inventors gives much more weight, in the regression, to patenting events beyond the first one.

The role of AVG_PUB is confirmed, but the time structure of DELTA_PUB looks somehow altered, as it is now the coefficient for current publications (DELTA) to affect significantly the hazard rate.

{TABLE 9 HERE}

The gender effect disappear, while the field dummies enter the regression in a different way (for ease of exposition, Biology is now the reference case). We first notice that both the dummies for Electronics and Pharmaceuticals affect directly, as a result of the higher number of multiple patents by academic inventors in the two fields. The field variable again interact with S_COPAT, but now it coauthorship within the field of Biology that seems to affect most the hazard rate (Chemicals is still the field whether coauthorship matters less). In addition, the field dummies interact with the PhD dummy: holding a PhD affects more heavily the hazard rate for Biology professors than for any other else.

5. Discussion and conclusions

The results of the analysis conducted in section 4 suggest that no major trade-off exists between patenting and publishing: academic inventors do not publish less than their colleagues with no patents, and do not show a bias towards more applied, less basic science. If possible, our results indicate the opposite, that is the existence of a positive link, by which more productive professors are more likely to end up signing one or more patents. In this respect, our results confirm the results obtained by Stephan et al. (2004) for the US case, while are at odds with Agrawal's and Henderson's (2002) findings in their case study of MIT.

We also find that professors who register, in a given year, an higher-than-average productivity are more likely to patent in the following year, which suggests patents to be most often the by-product of a fertile research project. If confirmed, this interpretation may also suggest that professors manage to publish (some of) their research results even before patenting, thus avoiding too long a publication delay. This association between patenting and publishing in the short run is in line with findings by Azoulay et al. (2004) and Markiewitz and DiMinin (2004). Contrarily to the latter, however, we do not find evidence of a weaker publishing-patenting association for business-owned patents as opposed to university-owned ones.

Scientific collaboration with industry, in the form of co-authored papers, affect the probability to patent with Business companies, possibly as a result of the same research from which the co-authored papers emerge. Academic fields such as Biology and Pharmaceutical, whose research results are more directly exploitable by industry, are those for which the effect is stronger. This results is in line with the broader literature on the importance of university-industry scientific partnership in the Pharmaceutical industry, and more generally in the science-based technology fields (Cockburn and Henderson, 1998).

Further research is needed to confirm and extend the results obtained so far. More accurate information on the CVs of both academic inventors and their colleagues is needed (especially on the level of their post-graduate education), as well measures of prestige and productivity at the department level. While common and easily available in the US, these data have to built from scratch from Italy (some attempts to build a general database have been under way by initiative of the Conference of Italian Universities' Rectors, but no longitudinal data are available).

If further work with richer data will confirm the results obtained so far, we will have proven that even in a weak system of innovation such as Italy, academic patenting is a non-negligible phenomenon, which does not occur to the immediate detriment of research. It remains to be seen whether academic inventors' research results, being protected by patents, are less likely to serve as the basis to further research by other scientists, who may be put off by the risk of infringement or the licensing costs (see footnote 3).

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APPENDIX

Table 1. Italian university professors in 2000, selected fields

Field	Professors, active in 2000	*of which*: Academic inventors, n. and (%)
Chemical eng. & Materials tech.	355	66 (18,5)
Pharmacology	613	84 (13,7)
Biology	1359	78 (5,7)
Electronics & Telecom	630	73 (11,6)
Total	2957	301 (10,2)

Source: EP-INV-DOC database

Table 2. Distribution (%) of academic inventors by n. of patents and field

	n. of patents			
Fields	1	2-5	6+	
Chemical eng. & Materials tech.	60,9	32,8	6,3	*100*
Pharmacology	63,1	28,6	8,3	*100*
Biology	70,5	23,1	6,4	*100*
Electronics&Telecom	56,2	31,5	12,3	*100*
Total	62,9	28,8	8,3	*100*

source: EP-INV-DOC database

Table 3. Ownership of academic inventors' patents§ by type of applicant and field; n. of patents (and %)

	Business	Open Science [1]	Individuals [2]
Chemical eng. & Materials tech.	127 *(76,0)*	22 *(13,2)*	18 *(10,8)*
Pharmacology	200 *(75,2)*	32 *(12,0)*	34 *(12,8)*
Biology	88 *(48,6)*	57 *(31,5)*	36 *(19,9)*
Electronics&Telecom	*200 (78,1)*	40 *(15,6)*	16 *(6,3)*
Total	615 *(70,7)*	151 *(17,4)*	104 *(11,9)*

[1] Universities, public labs and government agencies; both Italian and foreign.

[2] Same applicant's and inventors' names.

§ Patents owned by more than one applicant were counted more than once.

source: EP-INV-DOC database

Figure 1 - Distribution of publications per year, academic inventors vs controls; 1980-1999

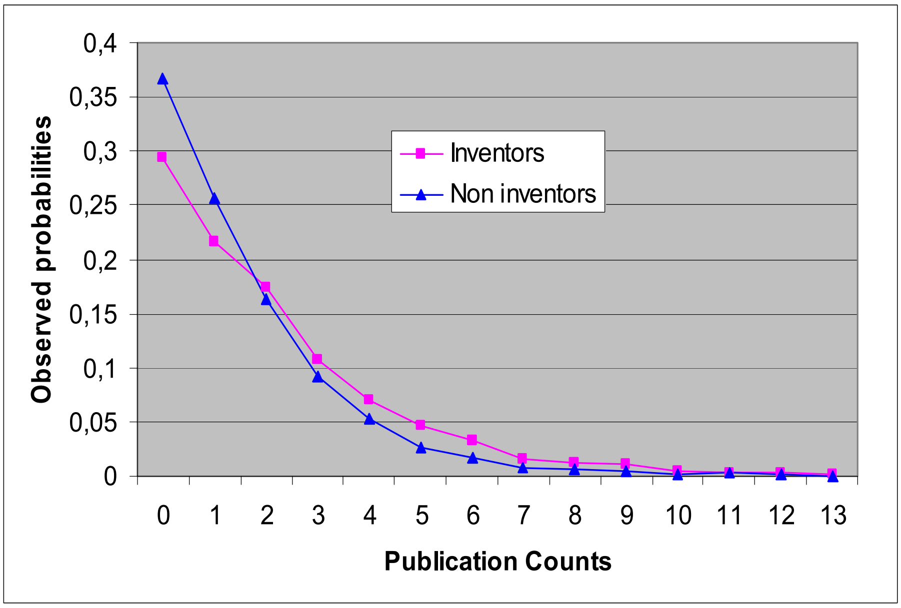

Table 4. Publications per year, inventors vs controls, 1975-2003; by field

	N	Mean	Std	Median
Inventors				
Chem.eng. & Materials tech. **	63	2,0	1,75	1,5
Pharmacology *	83	2,2	1,21	2,0
Biology *	78	2,5	2,10	2,0
Electronic&Telecom *	72	1,7	1,04	1,4
All Fields	296	2,1	1,60	1,8
Controls				
Chem.eng. & Materials tech.	63	1,3	1,10	1,1
Pharmacology	83	1,7	1,11	1,6
Biology	78	1,8	1,27	1,5
Electronics&Telecom	72	1,3	1,18	1,0
All Fields	296	1,6	1,28	1,3

** - ** Inventor-control distribution difference significant at .90 - .95 (Kolmogorov-Smirnov test)*
(1) Only professor aged 24-70 in current years
source: elaborations on EP-INV-DOC database and ISI Science Citation Index

Table 5. Descriptive analysis

Name	*Description*	*Obs.*	*Mean*	*Std. Dev.*	*Min*	*Max*
$DELTA\_PUB_{j,t}$	Difference between the yearly scientific production of a professors and his current Avg_Pub value	14538	.5121545	1.910365	-22	38.8
$AVG\_PUB_{j,t}$	Average number of publications at each point in time	14855	1.411994	1.388881	0	24
$DELTA\_BASIC_{j,t}$	Difference between the yearly scientific production (basic science) of a professors and his current Avg_Pub value	14538	.3622659	1.485924	-8	23.16
$AVG\_BASIC_{j,t}$	Average number of publications (basic science) at each point in time	14855	1.007724	1.15956	0	13.68966
$AGE_{j,t}$	Age of professors j at any time (time-variant)	14855	42.66254	10.71546	22	77
GENDER j.	Dummy variable equals 1 for woman professors	14855	.2098283	.4071997	0	1
$SHAREINV_{j,t}$	Share of academic inventors over the total number of a professor's department colleagues	14855	9.294453	11.02468	0	100
$CUMPATUNI_{j,t}$	Measures the stock of patents held by each professor's university at each point time	14855	43.90596	53.75198	0	226
$NUNI_{j.}$	n. of professors in hard science in university j in year 2000	14855	893.599	520.2939	18	2128
$USSDW_{j.}$	n. of professors in university j/n. of professors in Italy, by field	14855	5.59148	4.110059	.3424658	33.33333
$SSDUW_{j.}$	n. of professors in a given field in university j/n. of professors in university j, for each field	14855	2.103362	1.987298	.1104972	15.04425

Table 6 First patent (single event) – Estimated coefficients of the proportional hazard function (Cox model)

	(1)	(2)	(3)
	-0,01	-0,01	
DELTA_PUB$_{t}$	(0,936)	(0,028)	
	0,10	0,10	
DELTA_PUB$_{t-1}$	(0,035)***	(0,035)***	
	0,11	0,12	
AVG_PUB$_{t}$	(0,052)**	(0,051)***	
			0,03
DELTA_BASIC$_{t}$			(0,038)
			0,10
DELTA1_BASIC$_{t-1}$			(0,039)***
			0,09
AVG_BASIC$_{t}$			(0,059)
	-0,08	-0,08	-0,01
AGE$_{t}$	(0,09)	(0,009)	(0,312)
	-0,28	-0,27	-0,31
GENDER	(0,166)*	(0,160)*	(0,160)*
	2,54	3,51	3,43
S_COPAT$_{t}$	(0,407)***	(0,273)***	(0,271)***
		-1,00	-0,70
S_COPAT$_{t}$*DELEC		(0,443)**	(0,427)
		-8,52	-8,03
S_COPAT$_{t}$ *DCHEM		(4,042)*	(4,769)*
		-1,38	-1,30
S_COPAT$_{t}$ *DBIOL		(0,746)*	(0,735)*
	0,03	0,03	0,03
SHAREINV	(0,009)***	(0,008)***	(0,008)***
	0,001	0,0001	0,0007
CUMPATUNI$_{t}$	(0,002)	(0,002)	(0,001)
	0,001	-0,0001	-0,0001
NUNI$_{t}$	(0,0001)	(0,0001)	(0,0001)
	0,02	0,02	0,03
USSDW$_{t}$	(0,020)	(0,018)	(0,019)
	0,009	0,001	0,004
SSDUW$_{t}$	(0,032)	(0,031)	(0,031)
	-0,01		
ELECTRONICS dummy	(0,173)		
	-0,14		
CHEMICAL dummy	(0,200)		
	-0,02		
BIOLOGY dummy	(0,164)		
Wald chi-sq	79,74	351,66	353,66
Log-likelihood	-1755,99	-1755,99	-1754,42

*** 99% sign ** 95% * 90%

Breslow method for ties / Std errors adjusted for clustering on inventor

Obs. 9855 (592 subjects; 296 events)

Table 7 First patent (single event) – Estimated coefficients of the proportional hazard function (Cox model), by applicant type

	Business company (1)		Open Science institution (2)	
	(1)	(2)	(3)	(4)
DELTA_PUB	-0,02 (0,041)		-0,06 (0,059)	
DELTA1_PUB	0,07 (0,040)*		0,11 (0,055)*	
AVG_PUB	0,15 (0,052)**		0,14 (0,077)*	
DELTA_BASIC		0,02 (0,044)		0,04 (0,068)
DELTA1_BASIC		0,07 (0,047)		0,13 (0,056)***
AVG_BASIC		0,13 (0,070)*		0,09 (0,090)
AGE_t	-0,01 (0,010)	-0,01 (0,011)	0,11 (0,016)	0,10 (0,016)
GENDER	-0,56 (0,189)***	-0,60 (0,189)***	0,20 (0,265)	0,18 (0,265)
S_COPAT_t	4,19 (0,304)***	4,11 (0,304)***	0,97 (0,761)	0,92 (0,768)
S_COPAT_t*DELEC	-1,36 (0,436)***	-1,09 (0,434)**		
S_COPAT_t *DCHEM	-7,98 (4,336)*	7,52 (4,56)*		
S_COPAT_t *DBIOL	-1,65 (0,784)**	-1,60 (0,776)**		
POSTPAT	-0,40 (0,317)	-0,38 (0,317)	-0,28 (0,304)	-0,22 (0,302)
SHAREINV	0,03 (0,008)***	0,03 (0,008)***	0,02 (0,011)	0,02 (0,010)
CUMPATUNI	0,001 (0,002)	0,001 (0,001)	-0,0009 (0,003)	-0,0009 (0,003)
NUNI	-0,0003 (0,0002)	-0,003 (0,0002)	0,0002 (0,000)	0,0002 (0,0002)
USSDW	0,03 (0,020)	0,02 (0,020)	-0,04 (0,032)	-0,02 (0,033)
SSDUW	-0,04 (0,034)	-0,04 (0,035)	0,04 (0,047)	0,04 (0,047)
DELEC			0,45 (0,334)	0,58 (0,342)
DCHEM			0,12 (0,432)	0,21 (0,445)
DBIOL			0,87 (0,293)***	0,88 (0,290)***
Wald chi-sq	279,61	368,90	77,81	78,52
Log-likelihood	-1288,30	-1397,17	-572,41	-571,79

*** 99% sign ** 95% * 90%; Breslow method for ties / Std errors adjusted for clustering on inventor

(1) Obs. 10650 (592 subjects; 235 events); (2) Obs. 10650 (592 subjects; 94 events, including INDIVIDUAL patents)

Table 8 All patents (multiple events) – Estimated coefficients of the proportional hazard function (Cox model), by applicant type

	All applicants (1)	Business companies (2)	Open Science inst.(3)
DELTA_PUB	0,02 (0,022)	-0,01 (0,025)	0,06 (0,037)
DELTA1_PUB	0,05 (0,022)**	0,02 (0,025)	0,08 (0,038)**
AVG_PUB	0,14 (0,037)***	0,15 (0,046)***	0,31 (0,111)***
AGE	-0,01 (0,006)	-0,01 (0,008)	-0,01 (0,015)
GENDER	-0,39 (0,145)***	-0,71 (0,194)***	0,27 (0,361)
S_COPAT_	0,54 (0,804)	-0,29 (0,972)	-0,47 (1,316)
S_COPAT_ELEC	-1,98 (1,107)*	-3,16 (1,215)***	
S_COPAT _CHEM	1,98 (0,672)***	2,73 (0,810)***	
S_COPAT_BIOL	-0,02 (0,916)	-0,56 (1,108)	
STOCKPAT	0,03 (0,015)**	0,02 (0,016)	0,07 (0,034)**
SHAREINV	0,02 (0,004)***	0,03 (0,005)***	0,02 (0,010)
CUMPATUNI	0,003 (0,001)**	0,00 (0,001)**	0,00 (0,003)
NUNI	-0,0001 (0,000)	-0,0003 (0,000)*	0,0007 (0,000)**
USSDW	0,01 (0,013)	0,03 (0,017)*	-0,05 (0,047)
SSDUW	-0,03 (0,030)	-0,07 (0,040)*	0,03 (0,081)
DELEC			0,24 (0,498)
DCHEM			-0,14 (0,468)
DBIOL			0,45 (0,499)
Theta	0,36 (0,141)***	1,06 (0,258)***	6,42 (1,448)***
Wald chi-sq	190,86	137,73	57,38
Log-likelihood	3494,5334	-2926,0318	-968,62769
N. of subjects	1143	1144	1147
N. of failures	561	472	163
N. of obs.	11482	11482	11482
N. of groups	592	592	592

*** 99% sign ** 95% * 90%

Table 9. All patents (multiple events) – Estimated coefficients of the proportional hazard function (Cox model); inventors only

DELTA_PUB	0,05 (0,025)**
DELTA1_PUB	0,01 (0,028)
AVG_PUB	0,07 (0,030)**
S_COPAT_	4,56 (1,571)***
S_COPAT_ELEC	-2,99 (1,623)*
S_COPAT _CHEM	-6,49 (3,916)*
S_COPAT_FARM	-4,35 (1,771)**
PHD	0,86 (0,207)***
PHDELEC	-0,81 (0,391)**
PHDCHEM	-1,04 (0,399)***
PHDFARM	-0,86 (0,384)**
AGE	0,00 (0,011)
GENDER	-0,21 (0,179)
L1STOCKPAT	0,04 (0,028)
SHAREINV	0,02 (0,004)***
CUMPATUNI	-0,00001 (0,002)
NUNI	0,00001 (0,0003)
USSDW	0,02 (0,021)
SSDUW	-0,03 (0,049)
DELEC	0,74 (0,214)***
DCHEM	0,28 (0,259)
DFARM	0,51 (0,216)**
Wald chi2(22)	219,56
Log pseudo-likelihood	-1234,8218
N. of subjects	384
N. of failures	254
N. of obs.	2541

*** 99% sign ** 95% * 90%

Table A1. Disciplines (SSD) and fields; conversion table

Bio-chemistry (E05A)	Biology
Molecular biology (E05B)	Biology
Applied biology (E06X)	Biology
Human physiology (E04B)	Biology
Materials science and technology (I14A)	Chemical engineering & Materials technology
Macromolecular compounds (I14B)	Chemical engineering & Materials technology
Applied physics-chemistry (I15A)	Chemical engineering & Materials technology
Chemical engineering (I15B)	Chemical engineering & Materials technology
Industrial chemistry (I15E)	Chemical engineering & Materials technology
Electronics (K01X)	Electronics&Telecommunications
Electromagnetic fields (K02X)	Electronics&Telecommunications
Telecommunications (K03X)	Electronics&Telecommunications
Pharmaceutical Chemistry (C07X)	Pharmacology
Applied Pharmacology (C08X)	Pharmacology

Table A2. Institutional and personal variables, inventor vs. control sample year 2000

	University size [1]		Weight of the discipline in the univ. [2]		University weight in the discipline [3]	
	Controls	Inventors	Controls	Inventors	Controls	Inventors
Chemical eng. & Materials tech.	909 *	784	1,2	1,5 *	8,9	8,9
Pharmacology	947 *	910	2,0	2,1	4,9 *	4,6
Biology	896 *	869	2,6	3.0 *	3,9	4,0 *
Electronics&Telecom	834	939 *	2,7 *	2,0	5,2	5,7 *
All fields	898 *	879	2,0	2,2 *	5,5	5,6 *

[1] n. of professors in the university (all scientific discipline); avg values
[2] n. of professors in the discipline in the univ. / n. of professors in the university (%); avg values
[3] n. of professors in the discipline in the univ. / n. of professors in the discipline, all Italian univ. (%); avg values
* Mean value significantly higher at .90 (t test)
source: elaborations on EP-INV database and ISI Science Citation Index

Table A3. Personal variables, inventor vs. control sample year 2000

	Gender [1]		Age [2]	
	Controls	Inventors	Controls	Inventors
Chemical eng. & Materials tech.	14 (22,2%)	9 (14,3%)	51.55	51.60
Pharmacology	32 (38,6%)	27 (32,5%)	51.84	51.26
Biology	29 (37,2%)	20 (25,6%)	50.83	50.79
Electronics&Telecom	5 (6,9%)	2 (2,8%)	47.77	47.95
All fields	80 (27,0%)	58 (19,6%)	50.52	50.40

[1] n. of females (and % of total professors in the discipline)
[2] avg values
source: elaborations on EP-INV database and ISI Science Citation Index

Table A4. Top applicants of patents by academic inventors and patent concentration index, by field

Field/Applicant	n. of patents	*% over field*
Chemical eng. & Materials technology		
ENI Group	34	21,1
Montedison Group	16	9,9
Novartis AG	9	5,6
CNR (National Research Council)	9	5,6
Sisas Spa	8	5,0
	Herfindhal index (1-100)	*6,91*
Pharmacology		
Mediolanum Farmaceutici	19	8,4
SkyePharma PLC	17	7,5
Pfizer	14	6,2
CNR (National Research Council)	11	4,8
Lisapharma	8	3,5
	Herfindhal index (1-100)	*2,96*
Biology		
Istituto Angeletti	13	7,8
CNR (National Research Council)	11	6,6
MIUR (Ministry of Education & Research)	6	3,6
	Herfindhal index (1-100)	*2,13*
Electronics&Telecom		
ST Microelectronics	91	*37,4*
Optical Technologies	14	*5,8*
Selenia industrie elettroniche	12	*4,9*
Siemens AG	12	*4,9*
Universita degli studi di Roma "La Sapienza"	11	*4,5*
	Herfindhal index (1-100)	*15,55*

NB. Patents owned by more than one applicant were counted more than once; total number of patents in this table > actual total number

source: EP-INV database