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ACADEMIC INCENTIVES, RESEARCH ORGANIZATION AND PATENTING AT A LARGE FRENCH UNIVERSITY

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This article presents an empirical study on the patenting activities of the faculty members of the University Louis Pasteur, a major French research university. Our findings suggest that publishing and patenting are positively related whereas academic status and patenting are not, and that university researchers are more likely to patent later in their careers. With regard to research organization, we find positive effects of the laboratory's size, of the amount of contractual funds collected by the lab and of the share these funds received from private sources.

Keywords: Economics of science; Academic Patenting; Laboratory; University

JEL Classification: L31; 031; 032; 034; 038

1 INTRODUCTION

Patenting by US academic institutions has increased from about 250–350 patents annually in the 1970s to more than 3200 patents in 2001 (National Science Board, 2004). With such a sharp increase in university patenting (Henderson *et al.*, 1998; Mowery and Ziedonis, 2002), universities and other publicly funded research institutions are no longer considered as mere contributors to the increase in the stock of fundamental knowledge; they are increasingly seen as direct contributors to invention.[1] Thus, invention generation and technology transfer have become a major public policy issue and a concern for economic analysis.

Previous studies have shown that a local university tradition toward invention, the date of creation, the size and the organization of the technology transfer offices are important factors for explaining the success of a university's licensing activity (Berkovitz *et al.* 2001; Owen-smith and Powel, 2001; Siegel *et al.*, 2003). Very recently, the direct involvement of scholars has proven to be determinant in the success of technology transfer both from the point of view of universities (Jensen and Thursby, 2004) and from the point of view of firms (Thursby and Thursby, 2003a). This clearly calls for taking more carefully into consideration the strategies

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[1]The contribution of the academic sphere to invention can take different forms, e.g. the generation and diffusion of new ideas, sponsored research, companies hiring scholars (Mansfield, 1995; Cohen *et al.*, 1998; Zucker *et al.*, 1998). In the present article, we shall focus on patented inventions by academic scholars.

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of academic scholars who enjoy a large degree of autonomy in the time they dedicate to various research projects and to knowledge transfer. This also calls for a better understanding of the strategies of the various actors involved (the dean, the technology transfer office and scholars) and their complex relations (Beath *et al.*, 2003).

Whereas most empirical studies on academic patenting either focus on the university level of analysis (Foltz *et al.*, 2000, 2001; Coupé, 2003; Payne and Siow, 2003) or on the laboratory level (Azagra *et al.*, 2004; Carayol and Matt, 2004a), only a few very recent econometric studies analyse individual academics patenting behaviors. Agrawal and Henderson (2002) study the research production of a population of 236 professors employed by two departments of MIT in the year 2000 and who generated at least one paper or patent during the period 1983–1997. They focus on the relation between publication activities and patenting. Stephan *et al.* (2004) propose a study on patenting in the 1995 edition of the US Survey of Doctorate Recipients in which the latter were asked questions about their patenting activities. Thursby and Thursby (2003b) provide enlightening information concerning the invention disclosure behavior of faculty members at six of the top 50 universities in the United States. Even though the study of Wallmark (1997), dedicated to inventors' profiles at Chalmers University, does not provide any econometric evidence, it is also worth mentioning. Lastly, Lach and Schankerman (2003), though they use only university level evidence, provide a theoretical model that enables them to discuss the effects of royalty shares allocated to faculty on inventions and licenses incomes.

The present article constitutes a direct contribution to this burgeoning research area. It studies the determinants of patenting behaviors of nearly 900 academic scientists over the period 1995–2000 during which they were employed in a large research university which the Third European Report on Science and Technology Indicators (2003) ranked first among French universities in terms of impact, namely the University Louis Pasteur in Strasbourg. The novelty of our work is to go down to the level of individual academic researcher and to offer quite precise information on individual characteristics and the immediate research environment.

Our aim is to provide some precise information on who is involved in patenting activities in a (French) university, and on the mechanisms at play. Thanks to our detailed data, we have been able to carry out a study on how the regime of academic incentives (see, e.g. Dasgupta and David, 1994; Diamond, 1996; Stephan, 1996) and patenting behaviors interrelate. We try to determine whether the effects traditionally recorded for publication behavior affect patenting behavior in the same way or if different motives should be considered to understand scholars' patenting behaviors. We also attempt to determine how publishing relates to patenting. Moreover, our data enable us to analyse the effects of the collective organization of academic research on patent production. We raise questions such as: are larger labs intrinsically more or less productive? How does its funding structure affect patent production?

The article is organized as follows. The following section investigates the expected effects of individual characteristics on patenting, whereas the third section discusses the potential effects of lab research organization on patenting. The data is briefly presented in the fourth section. Section 5 introduces the simple econometric model of academic patenting behavior that we will consider and the estimation methodology. Section 6 presents the results which will be discussed further in the concluding section.

2 ACADEMIC INCENTIVES AND PATENTING

In this section, we consider the potential effects of individual characteristics (such as age, status and publication profiles) on patent production. For this purpose, we need to better understand the incentive regime scholars face. The implicit and explicit rules of academic research (Open

Science) stress a specific *reward system*, in which *priority* is essential (Merton, 1957). Peers collectively establish the validity and novelty of the knowledge produced (peer review). Peer recognition of a scholar as the 'intellectual proprietor' of the knowledge he has produced increases his reputation within the community (*credit*). In turn, scientific reputation translates into increased wages, more prestigious positions and other non-monetary rewards. Such a reputation-based system has two important implications on the distribution of incentives during researchers' careers. First of all, the individual returns on research activities are generally not immediate and are spread over the remaining professional cycle of the individual. Because the expected returns on human capital investments are logically decreasing with the remaining activity period, a decrease in research production during the life-cycle is predicted. Levin and Stephan (1991) suggested that scientists also have a 'puzzle solving' argument in their objective function: they do not only value wages but also scientific production itself. Then theory also predicts a non-linear inversed-U shape of scientific productivity over the life-cycle that was observed by Diamond (1986), Weiss and Lillard (1982) and Levin and Stephan (1991). The second consequence of such a reputation-based system is that it tends to concentrate attention and resources on the best-known scholars (Cole and Cole, 1973). The time series analysis of Allison *et al.* (1982) supports that such positive feedback process is at play in science. They find an increasing (linear) dispersion through time of research productivity between scientists belonging to the same cohorts.[2] (corrigé)

These two consequences of the reputation-based reward system provide academic scholars with very strong incentives in the early stages of their career. Therefore, if patents are not by-products of publishing and if patent production is not viewed by the community as a signal of research excellence, young researchers may not consider patenting as a relevant objective and may rather concentrate on publication activities. Simultaneously, older researchers may have a higher propensity to patent because they may value social wealth more (thus responding more to intrinsic motives than to academic incentives).[3] Another reason why older academics are more likely to patent is that the expected returns on inventions may be more immediate (even if also highly uncertain) than the returns on academic research which spread all over the remaining academic career. Moreover, such payments may extend beyond retirement. Thus older researchers' incentives to patent are all the higher, as incentives to publish decrease sharply. All this suggests that patent production should be increasing with age. This is what Stephan *et al.* (2004) found in their study.[4] Nevertheless, after conducting an exploratory panel data logit exercise, Thursby and Thursby (2003b) observed that age has a negative effect on the faculty invention disclosure probability. Such a difference might be explained by a non-controlled cohort effect in Stephan *et al.*'s study which is based on cross-section data. But we cannot find an intuitive explanation of such a cohort effect which should increase the probability of older researchers; indeed the literature normally shows that it is the younger scientists who tend to depart from the traditional norms of rapid and open disclosure (Dasgupta and David, 1994) and patent more. Since Thursby and Thursby (2003b) do not control for a potential non-linear effect of age, the negative effect of age they recorded might be mostly due to a general decrease in research outcomes in the late careers of individuals. Indeed they do observe an increase in patenting activities between the ages of 40 and 50 and a decline thereafter. Wallmark (1997) had also observed a peak in patenting around the age of 30–35 for Chalmers University researchers.

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[2] See Stephan (1996) and Diamond (1996) for surveys of empirical findings and Carayol (2003b) for a simple model of academic competition that introduces the two features of life-cycle effects and increasing advantages.

[3] Though this explanation is not fully consistent with the theory presented earlier, we cannot exclude this explanation.

[4] More precisely, they observe in several regressions that patents increase with the number of years since Ph.D. Since no age variable is included in their regressions, we can admit the number of years since Ph.D. to proxy age.

Let us now consider the possible effects of status. In France, permanent researchers may occupy two types of positions: either position as university professor implying both teaching and research duties or a full-time research position. The scholars occupying the former type of positions are employed by universities whereas the latter are employed by the large national public research organizations such as the CNRS[5] or INSERM.[6] Nevertheless both categories work together in university labs. The expected effects of the full-time research status *vs.* the teach-and-research status are ambiguous. On the one hand, we could expect patent production to increase when scientists occupy full-time research positions simply because these positions offer more time for research. On the other hand, the publishing performance of full-time researchers may be more strictly evaluated on the basis of their ability to publish in the best journals. Thus, they might be reluctant to dedicate too much time to patenting activities, as this might indicate that they do not dedicate enough time to fundamental research. Moreover, the faculty members who also have teaching duties may be more inclined to maintain relations with the industry so as to create job opportunities for their students (Stephan 2001). Thus, they may be more likely to be involved in applied research and to produce patents. In addition, researchers in both types of positions, are generally promoted halfway through their careers (from assistant professor and assistant researcher positions to full professor or director of research) on the basis of scientific accomplishments estimated through a peer review process. Promotion mainly implies a significant increase in wages and social status within the academic sphere. Nevertheless, it is not linked to tenure since, in France, assistant professors and researchers are tenured from the very beginning of their careers. The expected effects of promotion are ambiguous. Clearly, the incentives for faculty members to concentrate their efforts on academic activities (publishing) are high before they are promoted; but these incentives might not be as high once promotion has been awarded. Thus efforts dedicated to patenting should be lower before promotion if patent generation is perceived as requiring extra development time. Another reason why promotion should correlate with patenting is that promotion is likely to be awarded to researchers whose unobservable abilities are higher and likely to increase their propensity to invent. The preliminary results of Thursby and Thursby (2003b) tend to support the hypothesis of a positive effect of tenure (which would be the equivalent of our mid-career promotion) on invention disclosures. Nevertheless, in most of their estimations, Stephan *et al.* (2004) obtain the opposite effect, i.e. negative effects of tenure. This may be due to the decrease of research incentives in the late career. Indeed, if patenting simply results from a strong involvement in research, the traditional decrease of academic incentives in the late career also decreases patent generation.

Let us now discuss the relation between publication activities and patenting. On the one hand, we expect the most inventive researchers to have the best publishing profiles because both variables may in reality be positively correlated to unobserved individual characteristics such as ability or personal inclination to devote time and efforts to research. If we could control for individual fixed effects in a panel data context, we could raise the question of the specific effects of publishing on patenting performance. On the other hand, generating patents also takes extra time and thus patenting and publishing may crowd each other out in the short run. All in all, the relations between publication activities and patenting are ambiguous. Stephan *et al.* (2004) argue that it is possible to 'have the cake and eat it too', showing that the article counts are positively related to the number of patents invented. The study of Agrawal and Henderson (2002) on MIT faculty members shows that the effects of publishing on patenting are neutral. They indeed conclude that 'patenting activities do not appear to be significantly dependant on publishing activities' (p. 57). There may be a specialization process at work

[5] Centre National de la Recherche Scientifique (National Center for Scientific Research).
[6] Institut de la Santé et de la Recherche Médicale (National Institute of Health and Medical Research).

leading to crowding out between publications and patents in the long run. Some researchers may progressively specialize on research agendas that lead to a high publication performance whereas others focus on research purposes likely to generate patentable inventions. This specialization may be correlated to individual abilities: scholars certainly take into account the opportunity costs of patenting in terms of enhanced fundamental research and subsequent article production. Since opportunity costs are higher when scholars have higher abilities, scholars with higher abilities are more likely to specialize on research areas that will increase their chances of publishing articles in highly ranked publications. Scholars with lower abilities would specialize on research leading to lower ranked publications and patents. In order to estimate this process in the context of cross section data, a possible strategy is to estimate the effects of both publication counts and the average impact factor. Thursby and Thursby (2003b) tend to show that the faculty members who disclose more inventions both publish more and have a higher average impact factor. If confirmed, such a result would support the rejection of the hypothesis that a specialization process is at work.

This raises the question of the correlation between research strategy and patenting. Researchers may develop research projects that involve partnerships with researchers in industry. This behavior may correspond to a patent production strategy since working with industrial partners might reveal the needs for applied research, when a promising discovery is made, they may take the intellectual property rights on that invention (or shared property or even engage in license acquisition).[7] Lastly, patent production is more or less high depending on the nature of the discipline involved. Wallmark (1997) found that patents were unevenly distributed among Chalmers' schools: the Chemical Engineering department generates approximately one patent per professor, whereas the Physics Engineering department generates 0.14; and several schools generate none. It seems that researchers have very heterogeneous propensities to patent across domains.

3 RESEARCH ORGANIZATION AND INVENTION

This section discusses the expected effects of the collective organization of research on individual patenting performance. Innovation is often described in the literature as a collective process. Academic researchers are likely to benefit from the use of various resources available in their institutional and organizational environment so that organizational factors may affect individual patenting performance. A key issue, here, resides in selecting the appropriate level for the institutional and organizational environment, i.e. should it be the university or the laboratory?

The first organizational factor is related to potential scale effects. Coupé (2003) found decreasing returns to scale at the university level of analysis. Given the greater measurement errors at a lower level of aggregation, it becomes difficult to compute returns to scale at the laboratory level. Results are usually much more basic and the size of the lab is approximated by the number of permanent researchers (Bonaccorsi and Daraio, 2003). For instance, a negative impact of size on individual publication performance was observed by Carayol and Matt (2004b). The same question may be raised for patent performance. The literature provides contradictory results on the effects of funds received from different sources on university patenting. Payne and Siow (2003) show that federal funding has a significant positive impact. Foltz *et al.* (2000) find that the effect of federal (plus state) funding is positive and significant,

[7] It should be noted that in France, Universities and National Research institutions have the full rights over the results of publicly funded research. They can retain full property, share it, sell it, or even contractually let partners (usually private companies) acquire these rights.

whereas industrial and internal funding have no significant impact. In the particular case of agricultural biotechnology patents, the same authors find that only internal funding has an effect, whereas neither federal nor industrial funding do. Foltz *et al.* (2001) estimate a dynamic model on the restricted set agricultural biotechnology patents. They find that patenting experience produces more patents and that internal funding and state funding have a positive significant impact on patent production, whereas industry and federal funding does not.

One may argue that such ambiguous results on the effects of funding received from different sources are essentially due to the highly aggregated level of analysis retained (the university). Indeed, Crow and Bozeman (1987) underline that the nature of the research (applied *vs.* basic) is strongly influenced by the funding structure of the laboratory. From the detailed analysis of a set of collaborations between academic laboratories and firms in Europe and in the US, Carayol (2003a) shows that raising funds from private companies can be seen, at lab level, as a coherent strategy which also determines the type of research performed and the lab internal organization. Thus, it is relevant to analyse how labs are funded (on a competitive basis) so as be able to understand the potential effects of such specific lab strategies on faculty patenting. One intuitively expects researchers' patenting performance to increase with both the total amount of funds received by their labs and with the share of funds received from private companies.

4 THE DATA

The data concerns the research activity of a single university: University Louis Pasteur (ULP) of Strasbourg (France). ULP has a long tradition of fundamental research and of scientific excellence. Its researchers have been awarded many national and international scientific prizes, including Nobel Prizes. Overall, ULP is one of the largest French universities in terms of research. The Third European Report on Science and Technology Indicators (2003) ranks ULP first among French universities in terms of impact and 11th among European universities. Active researchers count one Nobel laureate, eleven members of the Institut Universitaire de France and eleven members of the French National Academy of Science. The university research capacities are reinforced by a close-knit relationship with the main national research organizations such as the CNRS and INSERM. Research and teaching activities cover a wide range of subjects: medical sciences, mathematics, computer science, physics, chemistry, life sciences, geology, geophysics, astronomy, engineering sciences and social sciences.

We collected the data from administrative reports completed in 1996.[8] These reports indicate the name, sex, age, status (full-time research or research-and-teach position, promoted or unpromoted) and discipline of 1,460 permanent scholars and researchers who were all present in the university in the year 1995.[9] Similar documents were compiled for the 2000–2004 period. Thus, we know who are the permanent researchers employed at the university in the year 2000. We excluded from our sample all researchers who were not included in the 2000 list so as to ensure that all individuals considered were present over the whole period considered (none moved to another university or retired within the period considered). At the end of the process, 941 fully informed scholars remained in the sample.

[8] Such reports are filed every four years. All laboratories (and also faculties and institutes) have to produce a standardized document.

[9] These contracts were signed in 1996 but prepared long before in order to be evaluated through peer review procedures conducted by both the Ministry of Research and Education and funding agencies such as the CNRS and INSERM whose support is expected. This is why data are assumed to be valid also for the year 1995.

TABLE I Description of the data on patent application families (concerns only period 1995–2000 and the 941 ULP scholars of the set).

	Number of patent families	*Number of ULP inventors*	*Number of invention occurences*	*Average number of inventors*	*Average number of ULP inventors*
epo_wo_fr	141	108	254	4.15	1.81
epo_wo_	113	97	212	4.29	1.83

The patent data comes from the French Institute of Intellectual Property (INPI) and includes all patent applications that were directly applicable in or later extended to France (mostly French, European and PCT patent applications).[10] We compared our initial list of permanent researchers with all inventors appearing in that set.[11] After a long data collection and cleaning process, we found 841 patent applications for our whole population for the period 1970–2000. This constitutes the first important result of our study: the invention function of the university as observed through patents is obviously much higher than anecdotal evidence from French universities suggests. Several measurement biases might have introduced such a misperception. Firstly, most studies do not fully account for the complexity of the French research system in which research units are most of the time affiliated to other research organizations. Such complexity renders outcomes difficult to attribute to given institutions the labeling of which is not sufficiently standardized. Secondly, some analyses are based on declarative survey data collected from the institutions themselves who are not aware of many inventions of their faculty members. Thirdly and most importantly, even when based on objective data, studies usually assume that the considered research institutions are among the owners (the applicants in the European system) of the patents that their staff contributed to invent. This assumption is not correct in the French case nor is it in other European countries as argued by Geuna and Nesta (2004).[12]

Among the 841 applications, 361 have been invented by at least one of our 941 researchers and have a priority date within the 1995–2000 period. The problem is that this set includes multiple counts since one invention can be the object of several applications. Therefore, we identified patent families which are defined by a unique priority number. For our study, we defined two types of families. The first ones, labeled epo-wo-fr application families, have at least one occurrence of a French, a European or a PCT application. The second ones, labeled epo-wo families, have at least one occurrence of a European or a PCT application. We found 141 and 113 of these two patent application families (from the 361 applications) that correspond respectively to 254 and 212 invention occurrences.[13] Table I provides more information on the number of occurrences, the number of ULP inventors, and the average number indicate, for each scholar, the number of epo-wo-fr and epo-wo application families for which his/her name appears in the list of inventors. These two will be our explained variables.

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[10] Therefore, we miss all patents applied in other countries than France, which did not use the EPO procedure in the first place and which were never extended to France. We are inclined to think that this set of patents is likely to be very limited.

[11] Thus we also miss all patents invented by non-permanents (PhD, post-docs). This set is also likely to be rather small since most of the time at least one permanent is among the inventors.

[12] In France, universities and national research institutions have for a long time had the right to retain intellectual property on the results of publicly funded research. In this respect, there was no need for a national equivalent to the Bayh – Dole Act. Nevertheless, in practice, academic scholars usually considered that patenting was out of their mission. The traditional pattern was the following: sponsored research contracts with private companies usually specified *ex ante* that property rights on potential inventions were the company's property.

[13] The number of invention occurrences are significantly greater than the number of patent families because co-invention between ULP scholars is frequent.

Information on the published articles of each permanent researcher in our database were also collected using SCI and SSCI ISI databases. More than 26,000 publication occurrences were recorded over the 1993–2000 period. We matched this table with our list of permanent researchers and dropped the articles that were not published over the period 1995–2000 (period during which we are almost certain they were employed in the university. By dividing each occurrence by the number of co-authors and calculating the total per author, we obtain the effective scientific performance corrected for co-authorship of each scholar considered. In addition, each publication item was associated with the impact factor of the journal in which it was published (given in ISI-JCR). This information makes it possible to correct each publication occurrence for impact. We can thus compute the weighted (for co-authorship) average publications impact of each scholar and his/her publication performance corrected for both co-authorship and impact. Figure 1 presents the distributions of the various publication measures and epo-wo-fr patent application families. We observe that the distribution of publication performance becomes skewer when impact is taken into consideration and that patent applications are much skewer than the distribution of publication performance.

Moreover, we know to which laboratories these permanent researchers were affiliated. We recorded 79 distinct laboratories in 1996 for which we have complete and reliable information. Thus, we can attach to each individual scientist the variables characterizing their laboratories. The number of permanent researchers in the lab is used as a proxy for the size of the lab. Lastly, we were able to collect precise information about the contractual funding of the laboratories (excluding wages). We collected information from the Technology Transfer Offices

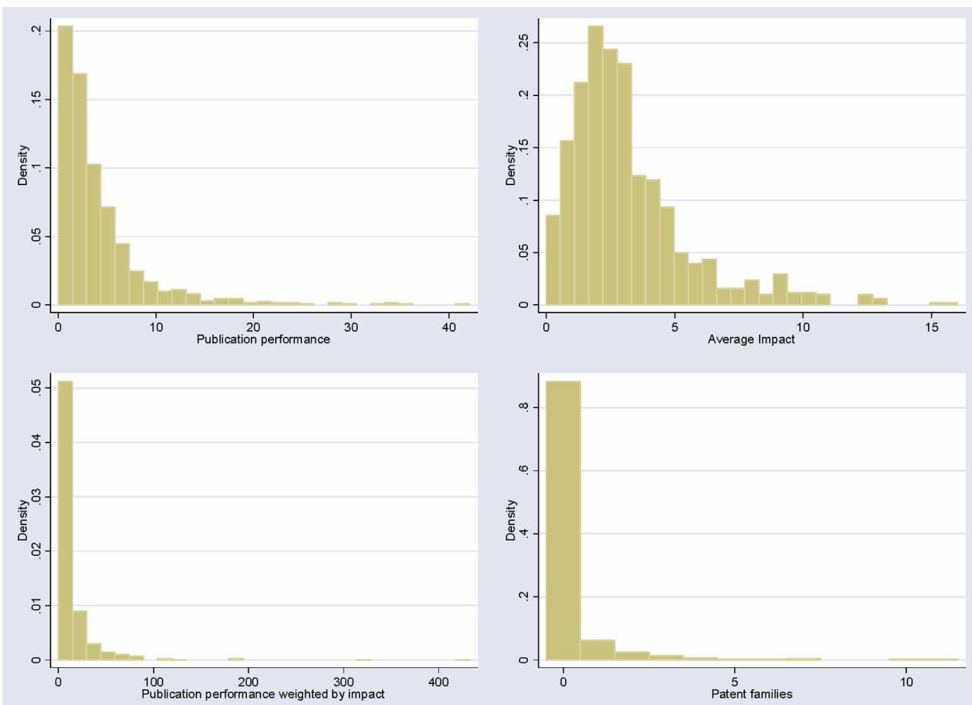


FIGURE 1 Distributions of the number of publication occurrences (*Perf*), of their weighted (by co-authorship) average impact (*Impact*), of the publication performance weighted by co-authorship and impact, and of the number of epo-wo-fr patent application families.

TABLE II Descriptive statistics on the variables for the 941 scholars of the data.

Variable	*Mean*	*Std. Dev.*	*Min*	*Max*
EPO_WO_FR	0.26	1.03	0	11
EPO_WO	0.22	0.87	0	9
Age1	0.18		0	1
Age2	0.31		0	1
Age3	0.37		0	1
Age4	0.15		0	1
Gender	0.23		0	1
Fulltime	0.55		0	1
Promotion	0.47		0	1
Perf	4.04	4.77	0.010	42.154
Impact	3.16	2.36	0	16.016
Indus	4.45	9.68	0	69.31
Lab. size	37.91	26.79	2	79
Funding	34469	50110	120	230721
Priv.fund	30.68	20.55	0	69.31
Disc1	0.05		0	1
Disc2	0.12		0	1
Disc3	0.18		0	1
Disc4	0.06		0	1
Disc5	0.07		0	1
Disc6	0.40		0	1
Disc7	0.09		0	1
Disc8	0.02		0	1

which administered contractual funding over the whole 1993–2000 period. The funds were differentiated according to the sources of funding, i.e. to whether they were public or private funds. Thus, for each lab, we computed the amount of funds received and the share received from private sources.

The variables are fully described in the appendix. Descriptive statistics on these variables are to be found in Table II.

5 MODEL AND METHODOLOGY

In the first sub-section, we present the zero inflated negative binomial (ZINB) model (Lambert 1992; Cameron and Trivedi, 1998; Greene, 1994, 2003; Winkelmann, 2003) which we use to mimic the invention phenomenon. The second sub-section presents the estimation technique and some specification tests.

5.1 The Model

Let the number of patented inventions of agent i be given by the positive integer random variable y_i (*EPO_WO* if only European and PCT applications are considered and *EPO_WO_FR* if French patents are also taken into consideration). We assume that patent production is the result of two superposed processes, such that y_i is given by the product of two other random variables as follows:

$$y_i = z_i \times y_i^* \tag{1}$$

The unobserved random variable z_i indicates whether i's research may lead to a patentable discovery or not. It is a dichotomous variable defined as follows:

$$z_i = \begin{cases} 1 & \text{if } i'\text{s research may lead to a patent} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

This variable is assumed to be determined by the vector of covariates $\mathbf{w}_i$ according to a given distribution function $F(\cdot)$ as follows:

$$\Pr(z_i = 0 \,|\mathbf{w}_i\,) = F(\gamma'\mathbf{w}_i) \tag{3}$$

This qualitative model is usually thought of as if there was another unobserved continuous variable (say z_i^*) at a given threshold of which z_i suddenly switches from one state to the other (from one to zero in this case). For our purpose, one may think of that unobserved continuous variable as the commitment to perform patentable research. When z_i is equal to zero, agent i is said to be in a non-patenting regime, whereas when z_i is equal to one, the agent is in a patenting regime. We shall further assume that $F(\cdot)$ is the Logit distribution:

$$F(\gamma'\mathbf{w}_i) = \frac{\exp(\gamma'\mathbf{w}_i)}{(1 + \exp(\gamma'\mathbf{w}_i))}$$

The unobserved random variable y_i^* accounts for the number of patents issued from patentable research. Let us consider that the arrival of patents is governed by a Poisson process which has been generalized in order to take into account the unobserved individual effects. Thus the expected number of patents for each agent i performing patentable research is given by:

$$E\left[y_i^*\right] = \beta'\mathbf{x}_i + \varepsilon_i = \ln\,\lambda_i + \ln\,u_i \tag{4}$$

with $\mathbf{x}_i$ the vector of independent variables and β the vector of its associated coefficients. The term $\varepsilon_i = \ln\,u_i$ stands for the unobserved individual effects. The distribution of y_i^* is given by the following density function:

$$f\left(y_i^*\,|\mathbf{x}_i\,\right) = \int_0^\infty f\left(y_i^*\,|u_i\,\right) g(u_i)\,\mathrm{d}u_i = \int_0^\infty \frac{\mathrm{e}^{-\lambda_i}\,(\lambda_i u_i)^{y_i^*}}{y_i^*!} g(u_i)\,\mathrm{d}u_i \tag{5}$$

with $f(y_i^*|u_i)$ the distribution of y_i^* conditioned on $\mathbf{x}_i$ and u_i (which is standard Poisson) and with $g(\cdot)$ the density function of u_i which is usually assumed to be Gamma ($u_i = \exp(\varepsilon_i)$: $\sim G(\theta)$) and normalized in order to have a mean equal to one ($E[u_i] = 1$) giving

$$g(u_i) = \frac{\theta^\theta}{\Gamma(\theta)}\mathrm{e}^{-\theta u_i} u_i^{\theta-1}$$

Equation (5) can thus be rewritten as follows:

$$Pr\left(y_i^* = j\,|\mathbf{x}_i\,\right) = f\,(j\,|\mathbf{x}_i\,) = \frac{\Gamma(\theta + j)}{\Gamma(j+1)\Gamma(\theta)} r_i^j\,(1 - r_i)^\theta \tag{6}$$

where $r_i = \lambda_i/(\lambda_i + \theta)$, which is the form of the negative binomial distribution. This distribution departs from the Poisson distribution which has a variance equal to the mean (λ_i).

Instead, we now have:

$$E[y_i^*] = \lambda_i \quad \text{and} \quad \frac{\text{var}[y_i^*]}{E[y_i^*]} = 1 + \frac{1}{\theta} E[y_i^*]$$

With regard the observed dependent variable y_i, the non-conditional probability of the observed number of patents is thus given by

$$\begin{aligned}\Pr(y_i = j|\mathbf{x}_i, \mathbf{w}_i) = {} & \Pr(z_i = 0|\mathbf{w}_i) \times (1 - \min\{j, 1\}) \\ & + \Pr(z_i = 1|\mathbf{w}_i) \times \Pr(y_i = j|\mathbf{x}_i, z_i = 1)\end{aligned}$$

with $j = 0, 1, 2, \ldots$

Knowing that the probability of the observed number of patents conditioned on a z_i equal to unity, is equal to the unconditioned probability of the unobserved random variable y_i^*: $\Pr(y_i = j|\mathbf{x}_i, z_i = 1) = \Pr\left(y_i^* = j|\mathbf{x}_i\right) = f(j|\mathbf{x}_i)$, and after trivial recombinations, we can write

$$\Pr(y_i = j|\mathbf{x}_i, \mathbf{w}_i) = F(\gamma'\mathbf{w}_i)(1 - \min\{j, 1\} - f(j|\mathbf{x}_i)) + f(j|\mathbf{x}_i) \tag{7}$$

The β coefficients appear in the $f(j|\mathbf{x}_i)$ through $\lambda_i = \exp\left(\beta'\mathbf{x}_i\right)$. This equation is the basic equation of the full model that we will estimate. This model is known in the literature as the zero inflated negative binomial model (from now on ZINB model). It is developed in Greene (1994, 2003), Cameron and Trivedi (1998) and Winkelmann (2003). We will also estimate another model which is nested in it, namely the negative binomial (from now Neg Bin) model for which there is no zero inflation ($\forall i, z_i = 1$).

5.2 Estimation Methodology and Tests

According to model (7), the log-likelihood which will be maximized is the following:

$$\begin{aligned}L = {} & \sum_{i \in S} \ln\left[F(\gamma'\mathbf{w}_i) + \left(1 - F(\gamma'\mathbf{w}_i)\right)\left(1 + \frac{\exp\left(\beta'\mathbf{x}_i\right)}{\theta}\right)^{-\theta}\right] \\ & + \sum_{i \notin S}\Bigg[\ln\left(1 - F(\gamma'\mathbf{w}_i)\right) + \ln\Gamma(\theta + y_i) - \ln\Gamma(y_i + 1) - \ln\Gamma(\theta) \\ & -\theta\ln\left(1 + \frac{\exp\left(\beta'\mathbf{x}_i\right)}{\theta}\right) + y_i \ln\left(1 - \left(1 + \frac{\exp\left(\beta'\mathbf{x}_i\right)}{\theta}\right)^{-1}\right)\Bigg]\end{aligned} \tag{8}$$

with S the set of individuals i having a non-null explained variable ($y_i > 0, \forall i \in S$).

Let us show that the use of the full model is justified on our dataset. First of all, a brief look at the data indicates overdispersion (see in Table II that we indeed have $\text{Var}[y_i] >> E[y_i]$ for both *EPO_WO_FR* and *EPO_WO*). Thus a simple Poisson model would not be appropriate. Such a phenomenon may be due to two non-exclusive phenomena: unobserved individual heterogeneity and/or zero inflation. In fact, together the zero inflated Poisson model (ZIP), the Neg Bin model and the ZINB model are natural candidates for us. The ZINB appears to be preferable to the ZIP model which is nested in it. The likelihood test of $1/\theta = 0$ ($\varepsilon_i = 0$) being equal to 32.61 for *EPO_WO_FR* and 20.51 for *EPO_WO*, the null hypothesis of no unobserved individual effect has been clearly rejected. In order to select between the

Neg Bin and the ZINB, let us write $h(\cdot)$ the density function of the ZINB (having $\mathbf{x}_i = \mathbf{w}_i$) given in Eq. (7) and define $m_i = \ln h(y_i\,|\mathbf{x}_i\,)/f(y_i\,|\mathbf{x}_i\,)$ (bearing in mind that $f(\cdot)$ is the negative binomial density function as stated in Eq. 6). Thus, we are able to compute the Vuong statistics (Vuong, 1989) as follows:

$$v = \frac{1}{\sqrt{n}} \sum_{i=1}^{n} m_i \Big/ \sqrt{\frac{1}{n} \sum_{i=1}^{n} (m_i - \bar{m})^2}$$

In our data, v is equal to 3.68 for *EPO_WO_FR* and 4.20 for *EPO_WO* which indicates that the ZINB model fits better for both dependent variables than the Neg Bin model. This legitimates the ZINB model on the data.

6 RESULTS

Even if the appropriate tests presented earlier fully justify the use of the complete model, we also computed standard negative binomial estimations in order to provide complementary information on the qualitative change between the patenting and the non-patenting regimes (by recording the effects of the explaining variables on patenting either assuming a regime change or assuming no regime change). We have two dependent variables: *EPO_WO_FR* and *EPO_WO*. Thus, we have four models. Model 1 and Model 2 have *EPO_WO_FR* as a dependent variable whereas Model 3 and Model 4 have *EPO_WO*. In the discussion of the results below the ZINB models (Model 1 and Model 3) are the preferred ones but we will often also refer to the two Neg Bin models (Model 2 and Model 4). The ZINB models (given in Eq. 7) have two parts: the negative binomial part (given in Eq. 6) accounts for the numbers of patents invented when individuals are in the patenting regime, whereas the Logit zero inflation part (given in Eq. 3) explains the switch between the patenting and the non-patenting regimes. Let us note that a positive coefficient in the zero inflation part of the model (gamma coefficients) means a higher chance to remain in the non-patenting regime, which implies zero patents. All model estimates are reproduced in Table III. The marginal effects for the four models computed at the mean of the independent variables are presented in Table IV. Significance levels are indicated here but should be interpreted with caution for the ZINB models since they are biased. It should be noted that the 65 scholars from Discipline 5 were not taken into account in these regressions because none of them generated a patented invention during the period.[14]

Our first series of results relate to age. We find that the scholars of the youngest cohort patent significantly less than the ones of the oldest cohort (which is taken into reference): in all regressions *Age1* dummy negatively correlates with patenting. We have significant and negative coefficients in the Neg Bin regressions (Models 2 and 4) and positive and significant coefficients in the zero inflation part of the ZINB regressions (Models 1 and 3). Therefore, the oldest scholars significantly differ from the youngest mainly in their choice between the patenting and the non-patenting regimes. Such results also apply to the two other cohorts (*Age2* and *Age3* as compared to *Age4*) only in the zero inflation part of Model 1 and in Model 4. Marginal effects tend to support this observation: the three dummies *Age1*, *Age2* and *Age3* have significant and negative marginal effects in all models (with the exception of *Age3* in Model 2). Since we do not use panel data, we cannot observe separately age and cohorts

[14] It might appear surprising that scholars from a discipline like engineering sciences do not generate patents. Nevertheless, they represent only 7% of our individuals. Moreover, at ULP, engineering sciences cover essentially physics engineering in which inventions are not necessarily fruitfully patented.

TABLE III Estimations on *EPO_WO_FR* and *EPO_WO*.

	EPO_WO_FR						*EPO_WO*					
	Model 1 (ZINB)						*Model 3 (ZINB)*					
	Negative binomial		*Logit zero inflation*		*Model 2 (Neg Bin)*		*Negative binomial*		*Logit zero inflation*		*Model 4 (Neg Bin)*	
	Coef.	*t-stat.*	*Coef.*	*t-stat.*	*Coef.*	*t-stat.*	*Coef.*	*t-stat.*	*Coef.*	*t-stat.*	*Coef.*	*t-stat.*
Age1	0.51	0.68	4.79*	2.89	−0.98**	−2.16	0.45	0.61	6.79**	1.96	−1.21**	−2.54
Age2	0.24	0.42	2.12**	2.14	−0.57	−1.50	0.04	0.08	2.77	1.21	−0.71***	−1.77
Age3	0.42	0.77	2.37**	2.03	−0.44	−1.53	0.21	0.34	3.25	1.22	−0.60**	−1.96
Gender	0.09	0.28	1.26	0.96	−0.27	−1.08	−0.07	−0.13	0.84	0.30	−0.29	−1.02
Fulltime	0.28	0.59	−1.39	−0.84	0.88*	3.54	0.44	0.59	−1.12	−0.41	0.83*	3.32
Promotion	0.66	1.21	2.27**	2.13	−0.04	−0.18	0.72	0.97	2.61	0.83	0.03	0.11
Perf	0.09*	3.83	−0.19**	−2.29	0.14*	6.31	0.08**	2.19	−0.35	−1.35	0.15*	5.56
Impact	0.00	0.07	−1.20***	−1.80	0.16*	2.71	0.04	0.78	−1.31***	−1.85	0.19*	2.89
Indus	0.09*	3.27	0.11	1.54	0.02**	1.97	0.09*	3.70	0.13**	2.29	0.02*	1.93
Lab.size	0.02*	3.68	0.02	0.60	0.02*	3.46	0.03*	1.92	0.03	0.43	0.02*	3.99
Funding	0.00**	−1.99	0.00	−0.11	0.00*	−2.68	0.00**	−2.54	0.00	−0.46	0.00*	−3.06
Priv.fund	0.02***	1.88	−0.05***	−1.88	0.04*	5.04	0.02	1.26	−0.08**	−2.23	0.04*	4.02
Disc1	1.98*	2.83	7.19*	2.74	−1.06	−1.42	1.87***	1.82	10.1**	2.21	−1.24	−1.49
Disc2	−0.41	−0.51	0.82	0.47	−0.65*	−2.67	−1.10	−1.21	1.23	0.45	−1.43**	−2.42
Disc4	2.31*	3.45	0.27	0.28	1.73*	3.22	3.05*	3.16	0.96	0.45	1.92*	3.03
Disc6	0.74**	2.44	2.42***	1.68	0.19	0.71	0.65	1.43	1.81	1.19	0.28	0.91
Disc7	0.35	0.62	2.99	1.21	−0.33	−0.69	0.77	0.88	4.65	1.39	−0.24	−0.43
Disc8	2.62*	2.77	4.52	1.49	0.22	0.33	2.83*	3.58	5.65*	2.78	0.44	0.67
Intercept	−4.84*	−6.57	−0.12	−0.07	−5.03*	−9.63	−4.78	−6.10	0.75	0.25	−5.25*	−8.55
$1/\theta$	1.71				3.87		1.55				0.81	

Note: The dependent variable *EPO_WO_FR* exhibits 768 zero observations and 108 non-zero observations and *EPO_WO* exhibits 779 zero observations and 97 non-zero observations (the 65 scholars from Discipline 5 are not included in the regressions). Concerning age cohorts and disciplines variables, coefficient should be understood as compared with *Age4* and *Disc3* modalities which are taken into reference. The standard errors of the estimates have been corrected to account for the fact that laboratory variables (*Lab.size*, *Funding* and *Priv.funding*) are equal for all scholars who are associated to the same lab.

*indicates that coefficients are statistically significant at the level 0.01.

**indicates that coefficients are statistically significant at the level 0.05.

***indicates that coefficients are statistically significant at the level 0.10.

TABLE IV Marginal effects for the four models at the mean of the independent variables.

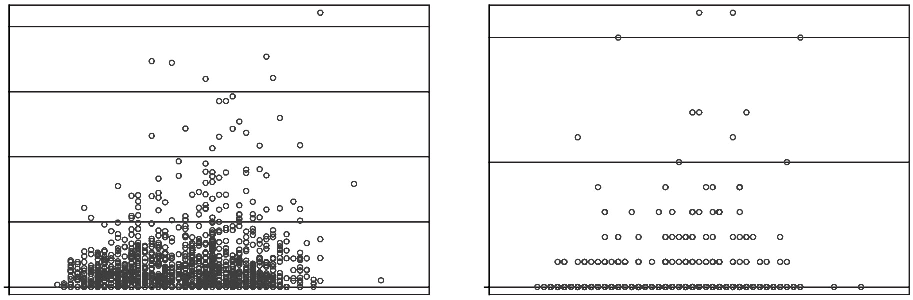
	EPO_WO_FR				*EPO_WO*				
	Model 1		*Model 2*		*Model 3*		*Model 4*		
	dy/dx	*t-stat*	dy/dx	*t-stat*	dy/dx	*t-stat*	dy/dx	*t-stat*	*Mean*
Age1	−0.208*	−4.57	−0.081*	−2.94	−0.189*	−4.30	−0.072*	−3.41	0.182
Age2	−0.126**	−2.18	−0.056*	−1.65	−0.150**	−2.02	−0.052***	−1.87	0.307
Age3	−0.116***	−1.89	−0.046	−1.60	−0.158***	−1.95	−0.046***	−1.92	0.363
Gender	−0.087	−1.39	−0.028	−1.14	−0.062	−0.53	−0.022	−1.11	0.228
Fulltime	0.155*	2.78	0.096*	3.64	0.130	1.44	0.069*	3.27	0.540
Promotion	−0.061	−0.89	−0.005	−0.18	−0.074	−0.84	0.002	0.11	0.469
Perf	0.031*	4.26	0.016*	6.12	0.034**	2.14	0.012*	6.11	4.122
Impact	0.096*	3.60	0.018*	2.63	0.096**	2.26	0.016*	2.78	3.258
Indus	0.006	1.25	0.002*	1.94	0.002	0.57	0.002**	2.02	4.492
Lab.size	0.003*	3.08	0.002*	3.56	0.002	0.71	0.002*	4.66	38.252
Funding	0.000	−0.51	0.000**	−2.52	0.000	−0.15	0.000*	−2.95	34976.3
Priv.fund	0.008*	4.84	0.004*	5.24	0.007*	3.86	0.003*	3.90	31.714
Disc1	−0.185*	−3.74	−0.076**	−2.30	−0.150*	−3.85	−0.063*	−2.61	0.056
Disc2	−0.112***	−1.92	−0.057*	−2.71	−0.137**	−2.15	−0.076*	−3.60	0.132
Disc4	1.208	1.54	0.450	1.60	1.137	0.95	0.424	1.42	0.068
Disc6	−0.065	−1.01	0.021	0.70	−0.042	−0.60	0.023	0.88	0.429
Disc7	−0.160***	−1.78	−0.032	−0.79	−0.141*	−2.66	−0.018	−0.47	0.099
Disc8	−0.113	−0.76	0.026	0.30	−0.113**	−2.23	0.046	0.55	0.024

Note: Concerning age cohorts and disciplines variables, coefficient should be understood as compared with *Age4* and *Disc3* modalities which are taken into reference.
*indicates that coefficients are statistically significant at the level 0.01.
**indicates that coefficients are statistically significant at the level 0.05.
***indicates that coefficients are statistically significant at the level 0.10.

effects. Nevertheless, we have strong reasons to believe that what we are observing here are true age effects rather than cohort ones. This is because we cannot find convincing argument to support the idea that younger cohorts are less likely to patent although the opposite is usually argued (the patenting behavior being more widely spread in the population of younger scholars). The effects of age on patenting recorded here differ from what is usually observed on publication performance: the oldest researchers patent more whereas publication activities decrease sharply in the late career. The older researchers may be more likely to engage in a patenting behavior because a longer experience (proxied by age) is required for patenting. This result may also indicate that older researchers tend to value patenting more than their younger colleagues.[15] Another complementary interpretation would be that, in their early careers, scholars tend to neglect patenting because they have to focus on publications. This corresponds to a career concern issue since it is known that early academic accomplishments strongly affect the professional career path. Later in their career, scholars are more prone to convert their scientific discoveries into patented inventions, i.e. into non-academic payoffs, or extra income that can extend beyond retirement.

Patenting and the effective academic career advancement of researchers do not appear to be closely related. We find that the mid-career promotion dummy (*Promotion*) is never significant with the exception of the zero inflation part of Model 1. This means that promoted scholars are less likely be in the patenting regime only when the French patent system is considered. The marginal effects are never significant. This supports the idea that patenting and career profiles are not closely related. This interpretation is also based on the results of

[15] High patenting performance is usually obtained between 50 and 60 years of age (cf. fig. 2 which also shows that there is an increasing diversity of patenting performance with age and that similar statements could be made on publication performance).

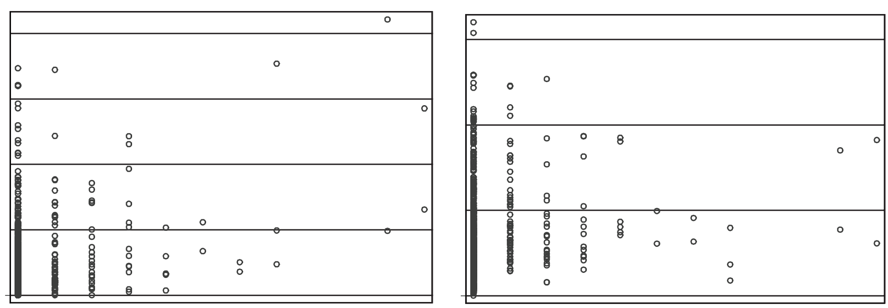


Age is in abscise.

FIGURE 2 Two way plots of age against the number of epo-wo-fr patent families invented (EPO_WO_FR) and against publication performance (Perf).

Carayol and Matt (2004b) who find (on nearly the same sample) a clear significant positive effect of promotion on publication performance. As regard the other explaining variable on the professional status (*Fulltime*), its coefficients are positive and strongly significant in the Neg Bin models (2 and 4) and not significant in the ZINB models. The marginal effects are positive and strongly significant in models 1, 2 and 4. The two regimes assumption of ZINB models lead to considerably weaken the significance of this variable. Therefore, it is difficult to draw any clear conclusion on the effects of this variable on patenting. Both the Neg Bin models results and the economic intuition would support the idea that the researchers who occupy full-time research positions are more likely to be involved in patenting activities because they are not subject to the same time constraints as those with teaching duties. Nevertheless, this effect is not so obvious and full-time research professional status does not seem to imply a strong patenting performance.

Even if patenting and publishing seem to occur at different periods in researchers' careers and even if the mid-career promotion is not clearly related to patenting (while publishing has proven to do so), in all estimations, patenting and publication performance are correlated (see also Fig. 3 for box plots of publication measures and patents). Publishing significantly increases the probability to reach the patenting regime in Model 1 and increases the patenting intensity within the patenting regime in Models 1 and 3. *Perf* also plays positively in Models 2 and 4. Thus, the less active researchers in terms of publishing is less likely to generate patented inventions. The weighted average impact of publishing (*Impact*) significantly and positively affects patenting in all models. Nevertheless, in the ZINB models, this variable



EPO_WO_FR is in abscise.

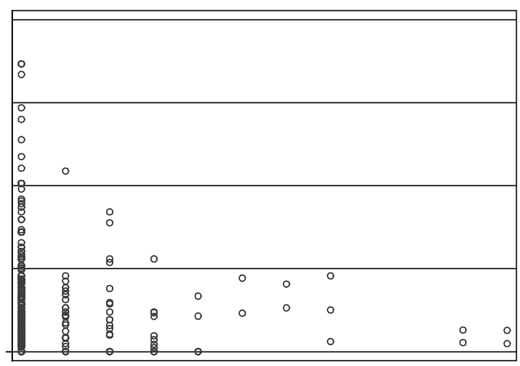
FIGURE 3 Two way plots of the number of epo-wo-fr patent families invented (EPO_WO_FR) against publication performance (Perf) and against publications average impact (Impact).

impacts mainly on the probability to choose the patenting over the non-patenting regimes or vice versa (negative significant coefficients in the zero inflation columns of Model 1 and Model 3). If impact is assumed to proxy research quality, then research quality appears to be an important factor in reaching the patenting regime. Thus, there seems to be no specialization process at work which would lead some researchers to focus on well-ranked publications and some others to specialize in patenting. Another (not necessarily a substitute) explanation would be that patenting occurs preferentially in more cited research areas (at the subdisciplinary level since we control for disciplines).

Does patent production imply a dedicated research strategy? In particular, does undertaking collaborative research with researchers employed in industry foster patenting? The answer to this question is clearly positive as shown in models 2 and 4 (positive and significant coefficients and marginal effects). It plays positively and significantly on patenting intensity within the patenting regimes of Model 1. Nevertheless, the answer to the question is unexpectedly mitigated in Model 3 because *Indus* also plays positively on the probability to remain in the non-patenting regime. Collaboration with industry might be frequent in some scientific fields in which patenting is not, whereas in other scientific fields collaborating with industry can increase the probability of patenting. The boxplot in Figure 4 is consistent with the idea that such a non-linear phenomenon is at play.

Let us now focus on the characteristics of the labs that favor patenting. It should be noted that the size of the labs has a positive and significant on the probability of being involved in patenting in all models. This result must be compared with the ones obtained on publication performance: The laboratory size usually affects negatively individual publication counts (Bonaccorsi and Daraio, 2003; Carayol and Matt, 2004b). Larger labs are necessary for patent production whereas small size affects publication performance positively. Moreover, size plays essentially on patenting intensity: in an invention regime, individual invention performance is higher in larger labs. This reinforces the idea that invention performance is higher in large teams whereas publishing performance is higher in a small team.

Lastly, lab contractual funding has a positive and significant effect on patents in all regressions. In the ZINB models, it plays only in the negative binomial parts. Thus when controlling for laboratory size, disciplines and the structure of funds (share of private *vs.* public sources), the amount of contractual funds increases the probability to patent of scholars who are in a patenting regime. The share of funds collected from private sources significantly and positively affects patenting in all models. It significantly favors both the patenting regime (*vs.* the



EPO_WO_FR is in abscise.

FIGURE 4 Two way plot of the number of epo-wo-fr patent families invented (EPO_WO_FR) against the propensity (transformed share) to publish coauthored papers with industry scientists (Indus).

non-patenting regime) and patenting intensity considering epo-wo-fr families (Model 1). As regard the epo-wo families, the share of private funds only has a positive and significant effect on the probability to be in the patenting regime (Model 3). Therefore, substituting private contractual funding to public funds seems to increase the probability to patent. Nevertheless, these results should be taken cautiously at this stage: the causality is not clear since, for instance, patenting researchers may also attract private funding more easily.

7 CONCLUSION

In this article, we have presented a study of the factors of patent production by faculty members working in the research laboratories of the University Louis Pasteur in Strasbourg. Both individual characteristics and variables related to their research laboratories are considered. Our estimations enable us to discuss how the academic incentives and the lab characteristics may affect the propensity to patent.

We find that career profiles, i.e. academic status, and patent production are not clearly related. Moreover, younger researchers patent less, whereas older researchers seem to be more likely to patent. The younger researchers are likely to focus exclusively on publication performance due to life-cycle and increasing returns effects. The older researchers may have their own motives to have their discoveries patented. Another explanation could be that the expected payoffs from patenting may be more immediate than the payoffs from purely academic research, and they provide an income beyond retirement. Thus researchers have incentives to patent in their late career when their incentives to publish are known to decrease sharply.

It should not be inferred from these results that publishing and patenting are exclusive of each other. We find that publishing and patenting go together when controlling for the professional status, which certainly absorbs a part of the individual abilities effects. Nevertheless, our study does not formally allow us to conclude that there is an effect of reinforcement between patenting and publishing. A causal inference is hardly sustainable here because publication is still likely to be correlated with the individual unobserved abilities.

The research organizations that support patenting differ from those that promote publishing activities. The probability of patenting increases in larger labs, whereas the probability of achieving a high publication count seems higher in a smaller lab. Thus even though there is no incompatibility between patenting and publishing at individual level, there might be some incompatibility between both activities at lab level.

Lastly, it is important to bear in mind that our evidence relates to one university in one country. Therefore, our results may not be generalizable as such and should be compared with similar studies performed in other countries.

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APPENDIX

The Variables

$EPO\_WO\_FR_i$: number of patent application families that i invented (or co-invented) during the period 1995–2000 and that have at least one occurrence either in the French Patent Office, in the EPO, or in the PCT patent system.

EPO_WO_i: number of patent application families that i invented (or co-invented) during the period 1995–2000 and that have at least one occurrence either in the EPO or in the PCT patent system.

$Age1_i$: dummy variable equal to one if i belongs to the first cohort of age ($Age_i \leq 35$) and zero otherwise. Similarly, $Age2_i = 1$ if $35 < Age_i \leq 45$, $Age3_i$ is equal to one if $45 < Age_i \leq 55$, and $Age4_i$ is equal to one if $Age_i > 55$.

$Gender_i$: dummy variable equal to one if the permanent researcher is a female.

$Fulltime_i$: dummy variable equal to one if i has a full-time research position in 1996 and zero if he occupies a teach-&-research position.

$Promotion_i$: dummy variable equal to one if the permanent researchers was 'promoted' (as Full Professor or Director of Research) in 1996 and zero otherwise.

$Disc1_i$: dummy variable equal to one if the scientific discipline to which the agent is affiliated is Mathematics, $Disc2_i$ stands for Physics, $Disc3_i$ stands for Chemistry, $Disc4_i$ is for Earth Sciences, $Disc5_i$ is for Engineering Sciences, $Disc6_i$ is for Biology, $Disc7_i$ is for Medicine and $Disc8_i$ stands for Social Sciences.

$Perf_i$: publication performance of i over the 1995–2000 window corrected for co-authorship (strict proportionality).

Impact$_i$: weighted (by co-authorship) average impact of i's publication occurrences over 1995–2000 window (Impact Factor of the journals given in JCR).

Indus$_i$: share of i's publications that were co-authored with at least one author who mentioned a company as his or her professional affiliation. Transformed by $f(x) = 100 \ln(1 + x)$.

Lab.size$_i$: the number of permanent researchers of the laboratory to which i belongs.

Funding$_i$: amount (in thousand Euros) of contractual support given to the lab over period 1993–2000.

Priv.fund$_i$: share of contractual funding received from private sources over the period 1993–2000. Transformed by $f(x) = 100 \ln(1 + x)$