Labour Mobility of Academic Inventors. Career decision and knowledge transfer.

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Abstract
This paper analyses academic mobility on the basis of the information held in the PatVal database on European inventors in six European countries. First, we show that the participation of university to patenting activities is highly underestimated when assessed exclusively in terms of ownership. Second, academic mobility is unevenly distributed across technologies, mostly in the bio-medical area, and across countries, mainly in the UK, Germany and the Netherlands. Third, we analyse labour mobility from academia to business. Duration models show that the younger researchers (with less experience and less seniority) are the more likely to move, and they tend to move very soon after the patent. Multinomial models show that the value and cumulativeness of patents boost the probability of moving to a company. Interestingly, in both model scientific productivity seems to have a negative impact on the probability of moving. Finally, our analysis indicates that a patent can be considered as a shock that provides the opportunity for an academic to decide what to do: to stay in academia or to move to a company. If the latter, that tends to happen in the first years after the patent was granted.

JEL Subject Classification: O3, I28, J6
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1. Introduction

The scientific research process produces several outputs that fall into three broadly defined categories: (1) new knowledge; (2) highly qualified human resources; and (3) new technologies (and new instrumentations). The existing literature mainly focuses on the transmission mechanisms and impacts of new knowledge, via codified research outputs such as patents (Jaffe, 1989) and publications (Adams, 1990; Crespi and Geuna, 2004) or via such inputs as expenditure on research and development (R&D) (Griliches, 1998). A large body of literature is devoted to analysis of the contribution of human capital formation to firm performance (Moretti, 2002, Sianesi & Van Reenen, 2002), but much less is known about the transfer of knowledge embodied in highly qualified human resources and new technologies.

Much of the literature on the transfer of new technology concentrates on examining the effects of new scientific discoveries on the innovative activities of firms (see among others Klevorick et al. 1995; Cohen et al., 2002; Arundel and Geuna, 2004). The main focus of these studies is on the impact or importance of information diffusion, and only marginal attention is paid to the transmission mechanisms. Given the tacit nature of knowledge it would be expected that one of the main transmission mechanisms of new (technological) knowledge, developed by the scientific system, would be researchers and scientists who participated in the scientific creation moving to other areas.

In recent years a few empirical studies have examined the mobility of high skilled labour (Almeida and Kogut, 1999; Moen, 2000; Rosenkopf and Almeida, 2003; Palomeras, 2004) and particularly the geographic aspects (regional localisation, US versus non-US firms), and the technological characteristics of the originating and receiving firms. Less is known about the mobility between academia and business. To our knowledge the only paper that develops theoretical and econometric analyses of the mobility of researchers between universities and firms is by Zucker et al. 2002 on the biotechnology industry. Little is known about academics' mobility in the European context.

This paper addresses the issue by analysing the determinants of mobility from the university for a sample of European academic inventors. We use the PatVal database, a unique database containing information about inventors from a sample of about 9,000 European Patent Office (EPO) patents issued in the mid nineties. Patents were sampled on the basis of their quality (in terms of citations and court litigations) and the mobility of inventors.

Papers such as Zucker et al.'s (2002) subsumed "real" labour mobility within the broader group of university–industry research collaborations. In this paper we focus on "real" labour mobility of academics, who after involvement in the development of a patented invention, become employees in (or owners of) a firm. This phenomenon is generally overlooked in much of the literature on career movements and knowledge transfer. Mobility of scientists is always referred to as one of the most important ways in which knowledge is transferred especially in the case of tacit knowledge embedded in the researcher and therefore difficult to codify and transfer (or purposely not codified to extract economic benefit from the move to a new job (Breschi and Lissoni, 2001)); however very little is know about it. Our unique database enables us to make the first quantification of this phenomenon at the European level and allows us to test a set of preliminary hypothesis about the characteristics of the mobile inventors that can shed some interesting light on the process on knowledge transfer from academia and on the career path of academic inventors.

Given the originality of the data, we can offer some preliminary evidence on European academic patenting focusing on: (1) What is the relative importance of patents owned by the university and patents where there is an academic inventor? (2) What are the technological and country specificities of European academic inventors? Next, on the basis of an original theoretical framework encompassing both factors relating to career move decision and knowledge transfer, we develop two sets of econometric models to assess the impact of some explanatory variables (such as academic inventors' profiles, network connections and knowledge characteristics) on the occupational choices of European academic inventors. First we estimate a simple standard discrete time duration model to explain the probability of moving and after this we use a competing risk model for the multiple decision problem faced by an academic researcher (move to a company or to another public research organisation).

The paper is organised as follows. In Section 2 we briefly present the literature and the theoretical framework that inform our econometric analysis. Section 3 introduces the data source and illustrates the basic characteristics of European university patenting. The econometric models of academic mobility and the main results are discussed in Section 4. Finally Section 5 offers concluding remarks and suggests paths for further research.

2. Knowledge transfer and academic mobility

Universities are increasingly been asked to play a more active role in the process of knowledge transfer. Over the last twenty years the US and EU countries' governments have developed a set of policies to create incentives for the transmission of knowledge from the university to society at large. The dominant policy view has been that the university does not play a sufficiently active role in the process of knowledge diffusion. New institutional agreements were set up to help the knowledge flow from the university and into firms' innovation processes.[1]

Patents have become to be viewed as the solution to the problem. Higher levels of patenting by universities would allow quicker and easier access to the discoveries made by academic inventors. Starting with the US Bayh-Dole act, followed by policies in the UK and more recently in other European countries, universities have been given the right to own and exploit patents arising from publicly funded research. Most universities have created specialist units, often known as Technology Transfer Offices (TTOs), which are devoted to the management and exploitation of university property rights.[2]

Given the poor returns from academic patenting, the recent policy and academic literature supporting third stream activities has embraced academic spin-outs as the way to efficiently transfer knowledge and also make money for the university.[3] In some studies spin-outs

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[1] Some of the literature has highlighted the far too simplistic model behind this view (e.g. knowledge is locked into the university, we simply need to find ways to release it), and the majority of policy actions informed by this view put pressure on universities to increase the supply of 'usable' and easily available knowledge. See Leydesdorff and Etzkowitz (1996) as an example of the normative literature arguing for the need to develop third stream activities within the university; while David et al. (1999), Geuna (2001) and Agrawal and Henderson (2002) are examples of works providing some evidence against the logic and potential of technology transfer in these new approaches.

[2] In the US there is increasing evidence that only a small number of universities are making any money out of their TTOs activities. See Mowery et al. (2004) for statistical and qualitative evidence on the small revenues (licensing income) generated at University of California, Stanford University and Columbia University, three of the most active universities in terms of patenting. See Geuna and Nesta (2005) for results for Europe.

[3] See Lockett et al. (2003) for a discussion of the UK situation and Di Gregorio and Shane (2003) for an analysis of the US developments.

represent large number of heterogeneous organisations. The early literature (see for example Stankievicz 1994), which was more interested in the broader issue of technology transfer than university intellectual property rights (IPR) management, considered spin-outs to be all companies that had some form of affiliation with the university, such as being set up by an ex-student or an employee of the university. The more recent literature tends to regard spin-outs as only those organisations where the university owns the property rights.

2.1 Academic mobility

While always acknowledged by the literature as being one of the most important mechanisms for knowledge transfer, little is know about the specificities of knowledge transfer via intellectual human capital. Some evidence has been produced from the few empirical studies that have examined the mobility of high skilled labour among firms (Almeida and Kogut, 1999; Moen, 2000; Rosenkopf and Almeida, 2003; Palomeras, 2004). However, for the academic sector, if we exclude the few analyses of mobility of post-graduate or post-doctoral students (Mangematin, 2000; Zellner, 2003), the only evidence comes from the series of studies published by Zucker, Darby and colleagues (see for example Zucker et al. 1998) on the impact and role of star scientists in the development of the US biotechnology industry.[4] Building on this research, Zucker and colleagues model the probability of a star scientist moving away from academia, including both part-time involvement in a collaboration with a company, and "real" full-time move to new employment within a company (Zucker et al. 2002).[5]

In this paper it is this "real" labour mobility of academics that we focus on. We try to explain the probability of a university employee moving to a different job following involvement in the development of a patent. More specifically, we want to identify what determines the different occupational choices made by academic inventors: to stay in the university, to move to a company (or create a new one), to move to another public research organisation (including another university, but also hospitals and government labs).

Using a search theory based model (Mortensen, 1987, Zucker, et. al, 2002, McVicar and Podivinsky, 2001), the decision to move from an academic institution to another job (either to a university or to a business firm) depends on two factors: the probability of getting a new job offer and the probability of accepting that job offer. That is, if we define an indicator variable M that takes a value of 1 if we observe mobility away from a given university we have that:

$$Pr(M=1)_{it} = \phi_{it}\eta_{it} \quad (1)$$

and ϕ_{it} and η_{it} denote the probability of receiving and accepting an offer respectively. Let us define:

$$\phi_{it} = f\left(X_{it}, Z_{it}, E_{it}, \phi\right) \quad (2)$$

[4] See the OECD report on Innovative People (OECD, 2001) for different approaches to human capital mobility.

[5] Most of the econometric results of the paper refer to the categories affiliated (working for a firm) and linked (collaborating with a firm) combined. No information about the relative weights of the two sub-categories is provided. Where results are for affiliated alone, the marginal effects are not significant. On the basis of these observations we conclude that the results of their paper relate more to collaboration rather "real" mobility.

$$\eta_{it} = g\left(w(X_{it}, Z_{it}), b(X_{it}), c(X_{it})\right) \quad (3)$$

Related to the determinants of ϕ_{it} and η_{it}, it is possible to think of a series of building blocks affecting some or all of them. In the typical search theory model (Mortensen, 1987), the probability of getting an offer is likely to depend of factors such as searching effort (ϕ), individual (X_{it}) and environmental labour characteristics (E_{it}). The probability of accepting an offer is likely to depend on the level of the wage offer (w_{it}) relative to the individual's current compensation (b_{it}) and other mobility costs (c_{it}). We do not have some observable measured of the "offered wage" (w) and of the "reservation wage" (b), however we can assume that earnings (both in terms of offered and reservation salary) depend on observable individual's characteristics (X_{it}). Finally (*Zit*) are attributes of the knowledge created by the research process and that is embodied in the researcher. These attributes characterise the process of knowledge transfer and create the incentives for the mobility of researchers when knowledge cannot freely circulate in codified forms. They affect both the probability of receiving an offer and the probability of accepting it.

Below we identify 6 building blocks explaining the mobility of academic inventors, the first three refers to traditional career path factors, while the last two pertain to the process of knowledge transfer. The forth is both of relevance for the understanding of career mobility and for the appreciation of mobility as a process of knowledge transfer.

First, the probability of receiving a job offer ϕ_{it} can be correlated with the *inventor's personal characteristics* (such as education, experience, number of previous patent applications and publications, etc.) that could be interpreted as signal of a high individual productivity. However, inventor's personal characteristics will affect both the salary being offered (w_{it}) and her opportunity cost, b_{it}. A key determinant of latter is the academic position of the researcher (we expect greater mobility from a non-tenured researcher and less from senior university staff). The higher the academic position, the higher the reputation and salary in the university leading to an increase in b_{it}, reducing the probability of moving out (to the extent that the increase in b_{it} is higher than the potential increase w_{it}). Inventor's personal characteristics can also affect the mobility costs c_{it}. A job change may require skill adjustments. If the skills by the inventor are university specific (i.e. some of the routines of the academic research work will be transferable to the work in a firm, while others are not), she should learn how to behave in a new organisation like a firm. She must learn new practices, protocols, routines and adjust to a different kind and pace of research, for example she will need to learn how to interact with product managers that intend to bring the product to the market as soon as possible. If this is true a period of training or adjustment must be required. Even if these adjustments are small, they can be considered as sunk costs and could deter some inventors to move. Similarly, the longer the inventor has worked in a given university the more she identifies with the incentive system and routines in that university and less willing she would be of continuing her academic career in another university. In particular, this could be true for mature academic researchers who have invested a lot of time in creating the skills and reputation needed to succeed in a specific university environment.[6] We can assume that the longer the inventor has worked in the university sector the more she will identify with the incentive system of 'open' science (Dasgupta and David, 1994) and the less likely she will be attracted to move to a firm by the offer of a particular salary. As a consequence, the effects of

[6] A related interpretation of mobility costs can be found in Shaw, K (1987)

experience and tenure would tend to increase both b_{it} and c_{it},(relative to w_{it}) reducing the probability to move. Finally, p*ersonal characteristics* based on past patterns: willingness to transfer and willingness to move also affect the mobility costs c_{it}. We can expect that the inventors that that have moved previously, may perceive moving costs as being less important than non-mobile inventors might. The research performance of the researcher is another factor affecting η_{it}. Publishing is a major determinant of academic rewards, although with differences across countries (certain European higher education systems relay less than others on research output as measure of quality) career and retention packages depend heavily on research output. Researchers with a good publications track will have higher access to retention packages and prospect of career; increasing b_{it} and affecting $\eta_{it.}$ However, previous research performance can be also read as a signal for high quality personnel, increasing both the probability of receiving an offer ϕ_{it} and the salary being offer w_{it}. The effect of previous research performance on mobility will be negative if their effects in b_{it} dominate its effect on w_{it}. Clearly other reasons related to career path are affecting the mobility from academia.[7]

Second, the inventor's employer can match the outside offer depending on the *retention strategy* developed by the university. A salary increase as a reward for patenting, share of the revenues from the patent, etc., would increase b_{it} leading to a less mobility. The Patval database allows identification of those patents that are owned by the university as distinct from those where a university employee is one of the inventors, but are not owned by the university (university-invented patents). We would assume that in the latter case the university is either not aware of the patent, or did not consider the invention worth patenting. In either case it would appear that the university does not have a retention strategy, and that as a result the probability of inventors with university invented patents moving will be higher..

Third, searching costs and hence ϕ_{it} also depends on the existence of a strong *potential demand*. Inventors working in universities in highly industrialised areas will be more likely to receive a job offer from a company or other university located near the university, and therefore will be faced with lower moving costs than inventors that move to a different region or country. If this is true, one can think that inventors living in more densely populated areas should have lower searching costs and hence higher mobility. However, inventors in large cities can also have higher opportunity costs to move. In Europe, the most highly reputed universities tend to be located in large cities, inventors from large cities will have both a higher c_{it} and b_{it} reducing η_{it}, making more difficult to them accepting the offer than inventors located in small cities.

Fourth, the more connected the inventor is to a densely populated *network* of public and private organisations the higher is the probability that she will move to another job as she will be well informed about positions that are available. This effect can be measured specifically at the level of the patent for example by the number of co-inventors and co-applicants and, more generally, by the collaborations that the inventor has been involved in before the patent was developed, which is a proxy of the density of the researcher's social network. In other words, social networks might work by increasing the inventor's probability of receiving an offer ϕ_{it}.

Fifth, we can think that ϕ_{it} will be an increasing function of the value of the knowledge created by the inventors. That means that, the probability of moving will depend on the

[7] For example in the US context junior faculty after about 7 years face the tenure assessment, if they are not successful they have to leave the institution. In Europe there are not so clearly defined rules, but some circumstantial evidence point to a 10 years career point in which the scientist can obtain the full professorship or face the decision of leaving.

expected value of the patent. As not all knowledge can be codified in the patent, hiring the inventor gives the new employer access to the inventor's tacit components of knowledge that she is unable or unwilling to transfer by means other than being mobile herself. Mobility from academia to companies is driven by this knowledge that willingly or not is imbedded in the inventor. We can expect that the higher the expected value of the invention the higher will be the salary that is offered (w_{it}), and hence η_{it}. Therefore the higher will be the probability of moving.[8]

Sixth, the *knowledge characteristics* of the specific patent and of the knowledge base of the inventor will also affect ϕ_{it}. Particularly, we refer to the degree of cumulativeness or separability of knowledge and its degree of generality or scope. We expect that a more cumulative (and less separable) knowledge makes the inventor a key element for technology transfer. That is, the more cumulative the knowledge of the inventor is, the more it is embodied into the inventor, making him more valuable and hence increasing the probability of mobility (by also increasing the offered wage w_{it}). A larger knowledge scope leads to more ambiguous predictions. On the one hand, a higher generality could mean a large scope and more possibilities (for the new employer) to innovate from a given knowledge, increasing the transfer value of the invention (Palomeras, 2004). On the other hand, high knowledge generality, interpreted as more basic knowledge, can require more complementary research to be carried to extract something from it, therefore decreasing the value of the transfer (and both ϕ_{it} and w_{it}).

Finally, it is important to acknowledge that R&D job markets are different in different sectors so the mobility will be different across technologies (e.g. higher in chemistry and pharmaceuticals than in other sectors). Similarly, regulation supporting or hindering mobility is different across EU countries resulting in different level of mobility across countries within the same sector.

Before presenting the econometric estimations, we introduce the data source and present a first set of descriptive statistics on European academic patenting.

3. Data source and description of sample

This paper uses the PatVal database, which includes information on more than 9,000 European inventors and their associated EPO patents. This database is based on a Europe-wide survey of inventors in the United Kingdom, The Netherlands, Italy, France, Germany and Spain with an EPO patent granted in the period 1993-1997.[9] The survey was conducted between July 2003 and April 2004. The primary goal of the PatVal-EU survey was to gather information on the economic value of European patents. However, the survey also gathered information on the characteristics of the inventors (such as their educational background, labour history, institution membership, etc.) and the characteristics of the invention process.

The total number of EPO patents between 1993 and 1997 was 49,078. When there were several inventors, the first inventor was contacted first. If no response was sent back, the

[8] The only reason why we can think of a higher patent expected value as being negatively correlated with the probability of moving is in those case were the opportunity costs also increases with the expected value. As we control in the regressions explicitly for retention strategy at university level we expect that patents expected value will have a positive impact on inventor mobility.

[9] For more information on the PatVal Project, see the PatVal report (European Commission, 2005).

second inventor was then contacted and so on. Most countries concentrated on a sub-sample of patents whereas others, like the UK, decided to send the questionnaire to all patent inventors. During PatVal, we contacted 27,531 patent inventors and we obtained responses for 9,017 patents. This equates to a 33% response rate (at the inventor level) and represents 18% of all EPO patents granted between 1993 and 1997.

Particular care was taken to produce an unbiased sample of respondents. As is the case with such studies, the PatVal large-scale inquiry ran the risk of over-sampling non-mobile respondents. This would be particularly harmful if mobility were the outcome of systematic characteristics of the population, such as human capital. It introduces the risk of under-sampling patents with higher-than-average economic value and, in our case, of underestimating the number of mobile university inventors. Hence, the survey made great efforts to reach mobile inventors through active searches of various information sources, mainly national directories and web sites. The final sample of 9,017 patents shows no bias in terms of patent quality (citations received and opposition) or patent technology classes.

Of particular importance is the institutional affiliation of the respondents at the time of invention. This information allowed us to identify patents involving university inventors other than by assignee name. Based on previous work (Geuna and Nesta, 2005), we distinguished between patents owned and invented by the university and patents with an academic inventor but which are not owned by the university of the inventor (university-invented patents). For example in the UK, 38 patents are assigned to a university but based on information from the PatVal questionnaire we found that 139 patents involved a university researcher. We found that in total 433 patents had a university inventor, which is 4.8% of the total sample. Table 1 presents patents by participation and property rights for both the whole sample and the university sample. We see that for the whole sample, almost 9 out of 10 patents (7,846 patents, or 87%) are owned by the employer of the inventor. However in the case of university patents, more than three quarters of the patents involving a university researcher (341 patents, or 79%) do not belong to the university (university-invented patents). This suggests that the importance of university patenting in Europe is largely underestimated and that this situation is considerably more widespread than is indicated by identification of the patent assignees, which is how it is analysed in most of the policy literature (see for example the recent OECD report on property rights in public research organisations, OECD, 2003).

{INSERT TABLE 1 APPROXIMATELY HERE}

Interestingly, the frequency of patent varies vary considerably across countries and technologies Looking first at the country distribution of university patents, UK universities are shown to patent significantly more than their European counterparts (139 patents, about 32% of university patents, almost the double of the UK share in the total sample) whereas the share of German decreases significantly by 12 percentage points compared to the total sample. In terms of aggregate technology classes (Table 3), university patents are mainly in the areas of chemistry and pharmaceuticals (36% versus 19%) and instruments (21% versus 11%), whereas the share of patents in mechanical engineering is significantly lower in our sample (from 30% to 10%). These variations across countries and technologies reflect specificities in both national and sectoral systems of innovations, such as the existence of incentive schemes for academic researchers, the entrepreneurial culture of public research organisation, and the uneven economic exploitation of scientific and technical advances (e.g. biotechnology).

Our main objective is to analyse the mobility of academic inventors. This requires that we refine our sample of 433 inventors in a number of ways. First, we exclude all patents mentioning the participation universities but for which the respondents was working in a private organisation at the time of the patent discovery process (139 observations). Second, we exclude inventors who were students at the time of invention (26 observations): a natural outcome of university graduation is to enter the job market. Third, we exclude all observations with missing or unusable information about job changes, regarding both the number of changes and the nature of the jobs. For example, we excluded all inventors who reported to have pursued their studies further, for this represents a move out of the job market. Likewise, respondents indicating that they moved, but not reporting *where* they moved to, were excluded. They may in fact have retired, but this does not represent job mobility. Fourth, we excluded all observations with missing values regarding the type of organisation that they joined. This produced a final usable sample of 230 observations, i.e. inventors, which we based our analysis on.

In Table 2, we report the type of organisation joined after patent application, reporting as additional information also on those inventors who did not move. It can be seen that the majority of respondents did not move after making a patent application. Also it can be seen that university inventors are slightly less mobile (81% versus 74%). This may reflect the nature of their positions, faculty researchers being civil servants in many European countries. Looking at mobile inventors only, the two samples exhibit very different patterns of mobility. Based on the entire PatVal database, 9 out of 10 inventors that move join a company (from large firms to self-employment). In the university sample, the proportion of inventors moving from academia to firms although still high (about 50%) is much lower than for the whole sample. As might be expected, university inventors are more likely to move to another PRO, and especially to another university (about 34%).

{INSERT TABLE 2 APPROXIMATELY HERE}

Tables 3 give further evidence of the specificity of the sample we used, based on distribution of technologies and countries across disciplines. Table 3 points to the particularity of the UK. Representing 17% of the PatVal sample, the UK share increases to 36% in the university sample, to finally 48% of mobile inventors. One in two mobile university inventors is from the UK, while France and Italy show the reverse pattern. In terms of technology, we observe no significant different in terms of professional mobility between the university and the whole sample. In fact, mobility is slightly higher in electrical engineering (increased share of mobile compared to non mobile). Rather surprisingly, the share of pharmaceuticals and chemistry remains constant (comparing mobile with non mobile): the share might have been expected to increase echoing policy makers emphasis on knowledge transfer in these technologies. Altogether, these preliminary results suggest that mobility is marginally influenced by technological fields, while there is an important country effect. This is not surprising: technologies should have an effect in terms of market (and job market) opportunities and countries are well known to adopt idiosyncratic systems of innovation. Moreover, the organisation of research is technology specific, and involvement of universities in downstream development varies widely from one discipline to another.

{INSERT TABLES 3 APPROXIMATELY HERE}

Table 4 displays the descriptive statistics, decomposing the full sample by types of sub samples. Note that the number of observations drops to 198 only. This drop combines the facts that first, some academic inventors had more than one patent and thus received more than one entry, and second, information concerning date of labour transition was missing or inconsistent for some other inventors. For the cases where inventors had more than one patent the median value was taken for the categorical variables and the mean value was computed for the continuous variables. We observe that 34 inventors are mobile (17% of academic inventors), with 19 going to a business organisation and 15 to another PRO. Whether these figures reveal a high or low labour mobility of university inventors in Europe is hard to say. As previously mentioned, this field of research remains generally unexplored, so that there is neither immediate nor authoritative benchmark. As for the feasibility of our econometric assignment however, these figures are very satisfactory, with an ideal split between "PRO-mobile" and "industry-mobile" inventors.

{INSERT TABLE 4 APPROXIMATELY HERE}

Table 4 shows a number of noteworthy preliminary results. First, mobile inventors have on average more valuable patents than non-mobile inventors. Observe that the mean patent value of "industry-mobile" inventors is lower than the mean patent value of "PRO-mobile" inventors, which seem at first sight counter intuitive. Second, we note that mobile investors have less experience, less tenure positions, a lower number of scientific contributions (publications and patents) and are less cited than their non-mobile counterparts. This suggests a strong individual life cycle effect on the career path. Third, some knowledge characteristics of the patent discriminate strongly between "PRO-mobile" and "industry-mobile" inventors having their mean value on opposite side of the full sample average. "Industry-mobile" inventors have less incremental and technologically narrower patents, suggesting that mobility to industry draws on both more radical and precise downstream developments. Finally, similar significant differences in networks oppose "PRO-mobile" with "industry-mobile" inventors, the former being part of a larger size of patent team on average and mentioning more frequently the participation of other organisations to the conduct of the patented invention (53% versus 16%).

4. Econometric models

We develop two sets of econometric models to evaluate the factors that affect the labour mobility of European academic inventors. First we estimate a standard discrete time duration model to explain the probability of moving and after this we use a competing risk model for the multiple decision problem faced by an academic researcher.

4.1 Academic inventors' labour mobility

This section presents the results of estimating the model specified above in order to study the impact of several covariates on academic inventors' labour mobility. Note that this is not the same as explaining the impact of patenting on academic labour mobility. In order to do this we would need a representative sample of academic researchers and information about their patenting behaviour. Our goal here is much more modest. We enquire into the determinants of labour mobility for a sample of *academic researchers* who are also *inventors*. That is, we follow the labour market behaviour of a given *academic researcher* from the moment that she has filed for a patent application, that is from the moment she became an *inventor* (Zucker et al. (2002).

We estimate a duration model for grouped data following the approach first introduced by Prentice and Gloeckler (1978) –*PG*-, where the discrete hazard time for individual i in time interval t to switch from the current job (exit) to a new one is given by a complementary log logistic –*cloglog*- function such as:

$$h(W)_{it} = 1 - \exp\{-\exp(W_i^{'}\beta + \theta(t))\} (4)$$

Where $\theta(t)$ is the baseline hazard function relating the hazard rate with the spell duration (Jenkins, 1995). In the empirical section, this function is approximated non-parametrically via set a time dummies variables that capture the influence of unobserved time varying factors affecting inventors' labour mobility. This model is the discrete time counter part of the Cox's proportional hazard model for continuous time (see Meyer, 1990). In order to estimate a model such as (4) it is necessary to re-organise the data set in such way that rather than the inventor being the unit of analysis, we use the spells at risk.

Before presenting the results we define the main variables of the model (represented by the vector W_i in (4)). In addition to including technology and country specific dummy variables, we consider the following explanatory variables defined according to the building blocks of the model specified in Section 2. For each building block we define the following variables:

1. Characteristics of the inventor:

   (i) *Gender*: A dummy equal to 1 if the inventor was a female.

   (ii) *Education*: Year of graduation minus year of birth minus 6.

   (iii) *PhD*: A dummy variable if inventor's highest academic degree is a PhD.

   (iv) *Experience*: Years of "potential" experience in the labour market before starting to work at the current university. Defined as year in which the inventor started working at the current university minus the year that she graduated from her highest degree (this variable includes also the years of not "proper" employment such as the years in which the researchers was unemployed or doing a post-doc).

   (v) *Tenure*: Years of working experience at the current university at the time of the patent application. Defined as the patent application year minus the year when the inventor started working at the university.

   (vi) *Mobility Before*: A dummy variable if the inventor answered positively to the question about previous employment in firms/organisations or had been self-employed.

   (vii) *Publications*: Total (cumulative) number of publications by the inventor up to the year before the patent application.

   (viii) *Citations*: Total (cumulative) number of citations up to the year before the patent application.

   (ix) *Past Patent Applications*: Number of European patent applications listed by the inventor so far.

2. Retention strategy operated by the university:

   (i) *Compensation*: A dummy variable if the inventor received any personal monetary compensation expressly because of the results of her invention.[10]

3. Potential demand:

   (i) *City*: Defined as a dummy variable if the inventor worked in a city of more than 100.000 inhabitants when the research leading to the patent was carried out.

4. Networks:

   (i) *Size of the Patent Team*: Number of inventors in the patent.

   (ii) *Co-ownership*: Number of applicants.

   (iii) *Collaboration*: This variable is built as a dummy if the inventor has answered that her co-inventors (if they existed) were employed by other firms in the private sector.

5. Value of the patent:

   (i) *Expected Patent Value*: This is the subjective value of patent according to the inventor's point of view. To be more precise, each respondent was asked to answer the following question "suppose that on the day in which this patent was granted, the applicant had all the information about the value of the patent that is available today. If a potential competitor of the applicant was interested in buying the patent, what would be the minimum price the applicant would demand?" The responses were structured in 10 asymmetric intervals ranging from less than E30.000 to more than E300 million. We took the natural log of the mean value of each interval plus the right border of the lowest interval and the left border of the top interval.[11]

   (ii) *Licensed:* A dummy variable that takes a value of 1 if the patent has been licensed by one of the patent holders to a third party.[12]

6. Knowledge characteristics of the patent:

   (i) *Cumulativeness*: A dummy variable if the invention builds in a substantial way on other inventions.

[10] In an analysis not reported here we also have used a dummy variable if the university owns the patent (university owned patent) expecting that in the case of university owned patents a the university is aware of the invention could develop some retention strategy. The variable was never significant, and as it was weakly positively correlated with the dummy for licence we have not included in this model.

[11] Although this is a subjective variable that could be severely contaminated by measurement errors, it has been extensively validated by the PatVal team and the results of this validation process seemed highly consistent (see Gambardella, et. al,, 2005).

[12] We have also tried with other proxies for value such as including the number of states where patent protection for the invention was asked for and the number claims in the last version of the granted patent, none of them were significantly different from zero.

(ii) *Patent Breadth*: Number of 4-digit technological classes (IPC) in which the patent was classified.

(iii) *Incrementality*: Number of backward citations for the patent.

For the cases where inventors had more than one patent the median value was taken for the categorical variables and the mean value was computed for the continuous variables. Although there are 206 academic inventors in the database, the estimation sample comprises only 198. Eight inventors were dropped due to inconsistencies in the information.[13]

Table 5 below presents the results of estimating several different versions of the duration model. The first column shows the result when the model is specified including only the baseline hazard function and a set of dummies by technological field. As can be seen, the class dummies are non-significant. In the second column, we add to the model three dummy variables according to country of the invention. These dummies should capture country specific factors affecting labour mobility. The base category in this case is an omnibus dummy for Spain, Italy and France. It was not possible to allocate individual dummies to these countries due to their very small numbers of mobile inventors. Thus, we included country dummies only for Germany, the Netherlands and the UK. It can be inferred from the second column that only the dummy for Germany was statistically significant and positive, meaning there was a higher probability of an earlier move from the current university for German inventors. This result is not robust to the different specifications: when controlling for inventor characteristics the coefficient of the dummy for the Netherlands increases significantly, and the effect becomes stronger than for Germany. The same sort of increase is also observed in the UK. Thus, according to the most extended specification (column 8), Dutch academic inventors showed the highest hazard to move in the sample, followed the Germany and the UK, in the three cases the findings were significantly different from the base category.[14]

The third column in Table 5 shows the results when controlling for the value of the patent. Looking at the "subjective" expected patent value, although positively correlated with the probability of moving, this variable only become significant when controlling for inventor's characteristics.[15] Regarding licensing, this variable is always positive but only significantly different from zero when controlling for the presence of compensation mechanisms.

[13] The inconsistency arises because they attributed the same year to the question about when they joined the university, and the question about when they joined their new employer after developing the patent. This seeming contradiction that might be because inventors were working part time in firms and part time in a university laboratory; however we do not have sufficient information to establish whether this was the case.

[14] It is important to notice that this result is not at odds with our findings in Table 3. It was shown there that UK was the country with the higher frequency of mobile inventors. However, that was a simple sample proportion that did not have taken into account how long each inventor has taken to move. The hazard rates given by the model (4) control for this fact by including a non-parametric time function $\theta(t)$. In summary, while in the descriptive analysis we examined if technological fields and countries had an impact on the mobility level, her we focus on explaining if and when the academics moves out of academia.

[15] Given the model's assumptions in order to have an idea of the economic impact of each one of the explanatory variable is necessary to take the exponential function of each estimated coefficient. For example, using the estimated coefficient for this variable, an increase of 1% in the expected patent value induces an increase in the hazard rate by 30% ($\exp(0.26)=1.30$).

The fourth column includes a set of proxies for the inventor's network. None of these proxies is significantly different from zero until we control for inventor's characteristics. In this case, the variable capturing collaboration with co-inventors working in the private sector becomes positive and significantly different from zero. This result indicates that those inventors working within a network of other researchers in the private sector are more likely to move to a new job in a company or other organisations.

The fifth column controls for the knowledge characteristics of the patent. Once again, none of these proxies are statistically different from zero until we control for the inventor's background. In this case those inventors that create highly cumulative knowledge are more likely to move from their current university employment. This result seems to confirm the view of researcher mobility as a unique knowledge transfer mechanism in the case of high cumulative knowledge. Cumulative knowledge is embodied in the inventor and therefore makes her the vehicle of knowledge transfer increasing her probability of moving to a new job.

The sixth column of Table 5 presents the results for the variables measuring the characteristics of the inventor. These variables tend to be highly significant. Firstly, we have some influence coming from life cycle effects captured by the fact that *education*, *experience* and *tenure* are significant and negatively correlated with the hazard rates, the younger the inventor is the quicker she is moving out. An additional year of education reduces the moving out of the current university. Similarly, inventors with more *experience* before entering their current university were also less likely to move.[16] Similarly, those inventors with more years of *tenure* in their current university, showed the lowest probability of moving. Additionally, those inventors that held a *PhD* degree were less likely to move, although this variable was not statistically significant. Contrary to our expectations, those that moved before were also less likely to move, although this variable was only marginally significant. In order to see if the combination of education, experience and tenure is only capturing life cycle effects, we have also re-run the model in column (8) with these variables replaced by age. The age variable was negative and strongly significant. However, the hypothesis that the coefficients of the three variables included in the un-restricted model (education, experience and tenure) were equal was rejected when testing using a LR-test with a P-value of 0.09. It seems then that a reduction of the three variables to age is rejected by the data. There is additional information in our current specification that is lost when the three included variables are replaced by age.

Finally, contrary to the results of Zucker et al. (2002), the scientific production (both in terms of quantity and impact/quality) of academic inventors does not affect the probability of moving. When publication and citation stocks are included in the model once at the time have both a negative but not significant coefficient (results not report here). When they are both included, such as in the result reported, none is significant although the inventors with a high publication record before the patent were more likely to move while those with a high impact/quality were less likely to do so. Similarly, a high inventive production does have a negative but not significant impact on the probability of moving. Overall, our results seems to indicate that are not the high-production/high-quality researchers that are moving, on the contrary it seems that the higher the scientific and technological output the lower the chances of moving.

[16] For example, using the estimated coefficient for this variable, an increase of one year in the inventor's previous experience induces a reduction in the hazard rate by 10% (exp(-0.10)=0.90).

Column seven of Table 5 controls for the potential demand. In this case the results indicate that those inventors working in large cities at the time of the patent application were less likely to move, although the results were not significant.

Column eight adds a control variable for the retention strategy at the university. Although negatively correlated with the probability of moving, this variable was not significant. This may also be due to the fact that the large majority of mobile inventors (about 70%) were associated with a university-invented patent, for which we would expect retention strategy to be less effective as the university is probably not aware (or not interested) in the invention.

{INSERT TABLE 5 APPROXIMATELY HERE}

Finally, there is the potential problem of individual level unobserved heterogeneity. Although we have already included a large set of control variables, it is expected that several other omitted ones also affect the probability of leaving the actual job. We have tested for this problem and fund that our findings are robust to the omission of unobserved heterogeneity.[17]

The left hand side panel of Figure 1 shows the baseline hazard function from the PG mode for pooled exits, calculated for the average researcher.[18] The plot suggests that there is non-monotonic negative time dependence in the hazard rates. In order words, the probability to exit the current academic job is very high soon after the inventor becomes at risk, that is, after the patent application has been filed. After this, the risk of mobility declines but only up to the fourth year, when we observed a second spike in exit behaviour. This spike lasts for about two years and it declines again by year 6. We do not have a final explanation for this pattern, but one option relates to the granting process when, after the application year, it normally takes 2 to 3 years to obtain a granted patent. Some inventors (the majority of the ones that decide to move), with highly valuable (and maybe technology complex findings) move immediately after the application, however there is a second group of inventors that might decided to wait until the application has been approved and the patent granted. It is interesting to analyse the plots of the hazard function. according to some of the individual characteristics. The right hand side of Figure 1 plots the hazard functions based on inventor's country of residence. The plots show that the probability of moving are very high in the years immediately after the invention applies to all the countries. However, there are interesting differences across the different nationalities. The highest exit probability, and hence the quickest mobility, is observed in the Netherlands, followed by Germany. The UK occupies an intermediate position. Finally, the mobility seems to be very low in the base categories (Italy and Spain). We could think that this pattern reflects profound differences in the academic labour market institution of the different countries, a statement that of course requires further research. According to the results from the corresponding survival functions (not shown here), while less than 1% of the Spanish and Italian researchers had moved after five years, the same rates where almost 10% for the UK, and about 25% for Germany and the Netherlands.

Figure 2 shows how the baseline hazard function varies according to changes on inventor's characteristics and expected patent value. The first two top panels show the baseline hazard function for an inventor without experience –e.g. she did not have a job before the current one- (left hand side) and for an inventors without tenure (right hand side), we have also drawn the mean hazard function in order to make the comparisons easier. It is clear from these two

[17] See Appendix 2 for the test.

[18] The average researcher has all the dummies set at 0, except for Process Engineering technologies and UK and holding a PhD, continuous variables are set to their sample means.

panels that inventors without experience and tenure have a higher probability of moving. The effects are larger for tenure rather than for experience. The bottom left panel compare the mean baseline hazard function with the one for the case of no publications (and citations). Both hazard overlaps almost perfectly suggesting the lack of relevance of these two variables to explain mobility. Finally the bottom right panel shows the hazard for inventors that produce patent with the expected value in the lowest interval (E 30.000). The hazard function for these inventors clearly suggests a higher probability of moving for inventors with high expected value.

{INSERT FIGURE I and II APPROXIMATELY HERE}

The results clearly indicate that traditional variables in models analysing career path such as the background characteristics of inventors are very important in predicting mobility. For example inventors with less experience, seniority and that are younger are likely to move to a new job sooner. Career path kind of explanations are, however, not sufficient in explaining the mobility of EU academic inventors. Knowledge transfer variables such as the expected value of the invention, the cumumativeness of the knowledge invented and the level of collaboration involved in the invention process also affect the mobility of inventors. We have found some evidence to support the view that the mobility of academic inventors is driven by career-path type determinants, and it also depends on the process of transfer of tacit knowledge embedded in academic inventors.

4.2 Modelling inventor's occupational choice

The pooled duration model estimated in the previous section does not take account of where mobile inventors move. In this last part of the empirical section we advance the analysis of the determinants of inventors' mobility controlling by sector of destination. We consider two potential sectors of destination for mobile inventors: at each given time an academic inventor must decide between staying at the current university, moving to another public research organisation –PRO- (e.g. another university, a government research laboratory or a hospital) or moving to a private company (either a large company, a small company or a new start up).[19]

The extension of the standard pooled duration model to two exit destinations is referred to as the *competing risks model* (CRM) (Jenkins, 2004; Boheim and Taylor, 2000). The two destinations are treated as independent, so the probability of exit towards a PRO is assumed not to depend on the probability of moving to a private company. We consider, that these two sectors offer different enough jobs to support this assumption (this assumption is tested below). In practical terms, the independent competing risk framework treats other exits as right censored (see Lancaster, 1990 and Jenkins, 2004). That is we estimate the following complementary log logistic model similar to (4), but where the full set of parameters is allowed to vary according the different destinations:

$$h(W)_{ijt} = 1 - \exp\{-\exp(W_i^{'}\beta_j + \theta_j(t))\} \quad (5)$$

Where, in our case *J=1 or 2* depending on if the mobility is towards a private company or to a PRO respectively. Finally, a cautionary note about the interpretation of the coefficient estimates. In CMR models, interpretations of the coefficients are not always as

[19] Ideally we wanted to split the private sector into incumbent firms and spin-outs, however this was not a feasible option because the very small number of cases in each of these sub-categories.

straightforward as in case of the pooled model of the previous section because the results depend on all the parameters in the model. If the CMR model has a proportional hazard form (as it is the case of (5)), then an increase in W will increase the conditional probability to move, let's say to a private company, if the estimated coefficient for the hazard of exit via a private company is larger than the corresponding coefficient in the hazards of moving to a PRO (see Thomas, 1996, for details).[20]

Table 6 shows the results of the CRM. Given the small number of exits to each one of the two destinations we have had to estimate a more parsimonious model than in the previous section. Hence, in order to reach identification, we have excluded from the model the variables number of applicants, number of inventor's previous patents, gender and we have had to merge both mechanical and process engineering dummies. The baseline hazard function, however, remains fully non-parametric.

First column of Table 6 re-produces the result of the single destination (or pooled) model. Column (2) and (3) show the results for the exits towards business and other PROs. The results show the three countries with higher mobility (Germany, Netherlands and UK) have a higher mobility towards private businesses in comparison to moving to another PRO, however this was only significant in the case of The Netherlands. A second interesting result is regarding the expected patent value. The finding indicates that inventors involved in more valuable patents have a higher probability to move to the private sector, while although patent value was also positive to predict moving towards other PRO, its estimated coefficient was 50% lower than in the case of business and not significant. In other words, high value patents increase the chances of moving towards a private business, leaving unchanged the probability of moving towards a PRO. We also found a similar result when value is measured according licensing.

A third set of findings regards networks effects. The results for collaboration indicate that academic inventors involved in collaborative networks (as measured by the fact of being involved in the invention with other co-inventors from a different organisation) have a higher probability of exit towards another PRO relative to exit towards a private firm. While, the finding that larger the size of the patent team the lower the chances of moving to a firm, may indicate that if the inventive process involve a too large set of researchers the knowledge developed my became easier to access by firms and therefore it reduces the chances of finding a job in a company based on the unique tacit knowledge of the specific academic inventor.

Regarding the knowledge characteristics we found that knowledge cumulativeness increases the likelihood of moving from academia towards business (the coefficients for cumulativeness are positive in the second column and negative in the third), however the results are not very significant. On the other hand, the spread of the knowledge (patent breath), as measured by the number reduces the odds of moving towards a private sector relative to moving to another PRO. In other words, while knowledge cumulativeness tends to increase the value of the tacit knowledge held by the inventors and therefore may have an impact only on the move to business, a high patent breath may result in difficult applicability reducing the attractiveness of those inventors for companies.

[20] It is worthy to say that specification (5) rests on the additional assumption that time is continuous but we only observe (grouped) time intervals and that the mobility is mainly concentrated at the edge of each interval. If we are willing to assume that we have intrinsically discrete time data we could also estimate (5) using a "multinomial logit" competing risk model. When estimated using this specification we found basically the same results.

The final set of result is regarding inventor’s characteristics. By comparing the results in columns (2) and (3) we can see that an increase in the inventor’s experience will reduce the likelihood of moving towards a PRO (less experienced researchers move to private businesses). Similarly, an increase in the number of years of employment in a given university will increase the probability of an exit towards a PRO respect the probability an exit towards business. In other words, conditioning on exiting current academic jobs, business firms tend to hire low experienced and more junior academic inventors. Finally, the results about publications are also interesting. The results for the CRM tends to indicate that, conditioning to exit, an increase in past publications tend to increase the probability of moving towards a private business, although inventors with high quality publications tend to move to another PRO. However, none of the differences among the variables was statistically significant.

It is also interesting to test whether the mobility to the two identified destinations, PROs and industry, are behavioural distinct rather than simply incidental. This is equivalent to the null hypothesis of equality of all parameters except intercepts in the models for the destination-specific hazard. Narendranathan and Stewart (1991) proposed likelihood-ratio type statistics for testing the following hypothesis:

$$H_0 : \beta_k = \beta_j = \beta \text{ and } \theta_k = \theta_j \quad \forall j,k \quad (6)$$

The test is given by the following expression:

$$2\left[\ln(L_{CR}) - \ln(L_{SR}) - \sum_j n_j \ln(p_j)\right] (7)$$

where $\ln(L_{cr})$ is the maximised log-likelihood from the competing risk model (the sum of those from the component models), $\ln(L_{sr})$ is the maximised log-likelihood from the single-risk model, n_j = number of exits to state j and $p_j = n_j \big/ \sum_j n_j$, where there are $j=1,\ldots j$ destination states. This test statistics is distributed Chi-squared with degrees of freedom equal to the number of restrictions[21]. Using information from Table 9 plus the above formulas, the Chi-squared value was 62.76 with a P-value of 0.00. In other words the hypothesis that the behaviours of both exit models are similar is strongly rejected.

The econometric analysis presented provides enough evidence to support the view that different factors affect the mobility of academic inventors depending on the organisation of their new job. On the one hand, for academic inventors that move to another PROs traditional factors related to the career of the academics such as experience, seniority and tenure play a major role. On then other hand, the mobility to a company is affected in a relevant way by factors related to the process of knowledge transfer. Variables such as the value of the invention and knowledge characteristics are needed to predict the mobility of academic inventors to business companies. We also have found some evidence suggesting that network effects are more important for the within PROs mobility.

{INSERT TABLE 6 APPROXIMATELY HERE}

[21] Note than given that the last term in (7) is strictly negative, thus the maximised likelihood for the competing risks model can be either larger or smaller than that for the corresponding single risk model.

5. Conclusions

This paper provides a first representative set of information on academic patenting in Europe. Our analysis is based on a sample of inventors of EPO patents, located in six European countries that produce a significant portion of innovative activities in Europe. On the basis of the information in the PatVal database, we have conducted a first analysis of the characteristics of European university patents in terms of ownership, technological class and country of inventor. The paper also analyses the mobility of university inventors, providing a first quantitative assessment of this phenomenon, and developing a set of econometric models to explain how different factors affect the mobility of European academic inventors.

We have identified that in total 294 patents had a university inventor, which is 3.3% of the total sample, only one third of these is owned by the university where the inventor was working at the time. European university patenting cannot be properly assessed and understood if the focus of analysis is on only patents owned by universities. The importance of university patenting in Europe is largely underestimated, it is considerably more widespread than is indicated by identification of the patent assignees, which is how it is analysed in most of the policy literature. Also, we found evidence that, as in the case of US university patents, European academic patents tend to concentrate more in the bio-medical area (and ICT area).

Academic inventors tend to be less mobile than company inventors, about 20% of academic inventors do move (in the ten years period following the granting of the patent) with a 50:50 split between companies and public research organisations. This paper does not analyse if this is a high or low level of mobility, however 10% mobility away from academia seems is a significant phenomenon at least for the sub-sample of university researchers that were the inventors of patents from the European Patent Office. A phenomenon worth studying to compare with the other knowledge transfer mechanisms in a view of improving the process of knowledge exchange between science and industry.

We have developed two sets of econometric models. First we have estimated a simple discrete time duration model to explain the probability of moving and after this we have used a competing risk model for the multiple decision problem faced by an academic inventor. First of all we have found some evidence that other things being equal academic inventors tend to have a higher probability of moving in the first years after the patent was granted; a patent can be considered as a shock that provides the opportunity for an academic to decide what to do: to stay in academia or to move to a company. However, we can not rule out the possibility that mobility is the result of a process of self-selection by those academic researchers that were not so good or interested in academia and that decided to invest in patenting so that they could then move and obtain a better job somewhere else. The consequence of this would be a bias in the baseline hazard function. We have investigated the effects of this sort of unobserved heterogeneity and we did not find strong evidence that this is affecting seriously our results.

Among other results confirming previous works, the econometric models provide some evidence indicating that that the more valuable is the patent the higher is the probability of moving to a company. Also, we found that the younger academic inventors (with less experience and less seniority) are the more likely to move, and they tend to move very soon after the patent. The more cumulative (or incremental) knowledge is the higher the probability of moving to a company. Contrary to results of previous studies, we found some evidence of a negative impact of scientific productivity on mobility. Estimations including the number of citations tend to confirm the result that highly productive academic inventors (both in terms of quantity and quality/impact adjusted) tend to have a lower probability of changing their academic job and especially to move to a firm. Finally, different factors explain the mobility to firms compare to the mobility to PROs.

The fact the value of the patent effect mobility can be due to the fact that when firms expect a high value (high potential returns) from the patent they want to be sure to have as much knowledge about the invention as possible (in most of the cases they already own the patent). So they tend not to have enough of the codified part given by the patent, but they want also to appropriate of the tacit part embedded in the academic inventors, and thus they hire her. In a similar vein the indication that inventors with patents characterised by cumulative/incremental knowledge tend to have a higher probability of moving seems to indicate that when the patents build on previous knowledge of the inventor the company has incentives to try to higher the academic inventor to appropriate of her tacit knowledge.

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Appendix 1: Variables description

Variable Name	Measure
Expected Patent Value	The expected patent values estimated by the inventor herself
Cumulativeness	Dummy variable set to 1 if the invention builds substantially on prior work by the inventor
Patent Breadth	Number of 4-digit technological classes (IPC)
Incrementality	Number of backward citations
Gender	Gender of the inventor
Experience	Number of years of experience in the labour market before starting work at university
Tenure	Number of years of working experience at the university
Publications	Number of past publications prior to patenting
Past Patent Applications	Number of past patent applications prior to patenting
Citations	Number of citations to scientific papers of inventor, normalised by the number of publications
Size of Patent Team	Number of co-inventors involved n the patent
Collaboration	Dummy variable set to 1 if the inventor has answered that her co-inventors were employed by other organisations.
Compensation mechanisms	Dummy variable set to 1 if the inventor received any personal monetary compensation expressly because of the results of her invention, 0 otherwise.
City	Dummy variable set to 1 if the inventor worked in a city of less than 100.000 inhabitants at the time of research

Appendix 2: Test for unobserved heterogeneity

What happens to parameter estimates if one (mistakenly) ignores unobserved heterogeneity? The theoretical literature has suggested two results. First, the (increasing) time trend capture by the dummy variables in (4) will be underestimated. This is basically a selection effect. To see these think that there are two classes of researchers: slow and fast movers. As time pass by, the conditional sample contains more and more slow mover researchers and hence generating lower hazard rates. Second, the presence of unobserved heterogeneity attenuates the proportionate response of the hazard to variation in each independent at any time (Jenkins, 2004 and Lancaster, 1990). To see how important these biases are we follow the standard practice in duration analysis and re-estimate (4) by including an individual level random effect. In order to investigate whether this problem existed here we re-specified model (4) as follows:

$$h(W)_{it} = 1 - \exp\left\{-\exp\left(W_i^{'}\beta + \theta(t)\right) + \varepsilon_i\right\} \qquad (5)$$

where ε_i is an unobserved individual-specific error term with zero mean, uncorrelated with the Ws. Model (5) can be estimated using standard random effects panel data methods for a binary dependent variable, under the assumption that some distribution is provided for the unobserved term. In our case, we will assume that the ε_i are normally distributed. The results of this estimation are shown in column 9 of Table 8. It can be seen that the results barely changed. In order words, our findings are robust to the omission of unobserved heterogeneity. This is also confirmed by the fact that we could not reject the hypothesis of lack of intra-subject correlation. It is important to say that some recent papers in the empirical literature on duration models have suggested that if a fully flexible specification for the baseline hazard function is used, then the magnitude of the biases in the model with omitted unobserved heterogeneity are diminished (Arulampalam and Stewart, 1995).

One remaining issue is about the impact of unobserved heterogeneity in the CMR model. On this issue, McVicar and Podivinsky (2001) and Boheim and Taylor (2000) argue that the distributional assumptions for including unobserved heterogeneity are even stronger in the CRM than in the standard single risk case, are therefore reluctant to assume any particular specification for such heterogeneity in their model. Roed et. al (1999) add that the standard negative bias on duration dependence of unobserved heterogeneity does not necessarily hold in a competing risk framework. Because of this, and considering the results for including unobserved heterogeneity presented above, we have not implemented this sort of correction for the CMR model.

Table 1
Participation & Owned Patents versus Participation only

Country	Respondent Frequencies			
	PatVal Database		University Sample	
Participation only (University invented patents)	1,010	11.2%	356	82.2%
Participation & Owned Patents	7,846	87.0%	77	17.8%
Missing value	161	1.8%	0	0%
Total	9,017	100%	433	100%

Table 2
Organisation joined *after* patent application

Type of organisation	Respondent Frequencies					
	PatVal Database			Analysed University Sample		
Large firm (more than 250 employees)	826	9.2%	43.6%	8	3.5%	18.2%
Medium firm (100-250 employees)	174	1.9%	9.2%	1	0.4%	2.3%
Small firm (less than 100 employees)	359	4.0%	19.0%	4	1.7%	9.1%
Self Employed (spin-outs)	335	3.7%	17.7%	9	3.9%	20.5%
Hospital, Foundation, or Private Res. Organization	13	0.1%	0.7%	1	0.4%	2.3%
Government Research Organization	33	0.4%	1.8%	5	2.2%	11.4%
University and education	90	1.0%	4.8%	15	6.5%	34.1%
Other Government	10	0.1%	0.5%	0	0.00%	0.00%
Other (Unknown)	54	0.6%	2.9%	1	0.4%	2.3%
Non-mobile	6,645	73.7%		186	80.9%	
Missing value	478	5.3%		0	0.0%	
Total	9,017	100%	100%	230	100%	100%

Table 3
Share of country and technology class by the mobility of inventors
Percentage, excluding missing values

	PatVal Database		Analysed University Sample	
	Non mobile	Mobile	Non mobile	Mobile
Country				
Germany	40.6%	25.0%	22.1%	25.0%
Spain	3.5%	1.3%	5.3%	1.0%
France	18.2%	11.8%	17.4%	8.0%
Italy	14.0%	13.8%	8.4%	7.0%
Netherlands	11.8%	15.4%	15.8%	11.0%
United Kingdom	12.0%	32.6%	31.1%	48.0%
Technology				
Electrical engineering	14.9%	18.9%	12.9%	18.2%
Instruments	10.5%	12.3%	26.3%	22.7%
Chemistry, Pharmaceuticals	19.2%	16.7%	30.7%	29.5%
Process engineering	25.5%	24.0%	20.4%	20.5%
Mechanical engineering	30.0%	28.2%	9.7%	9.1%
Total	100%	100%	100%	100%

Table 4
Descriptive statistics by type of mobility

	Full Sample	Non Mobile	Mobile	Mobile to Business	Mobile to PRO
Number of Observations	198	164	34	19	15
The EPO Patent value					
Expected Patent Value (Log)	6.34	6.31	6.50	6.15	6.96
Knowledge characteristics of the patent					
Cumulativeness (Dummy)	0.45	0.43	0.53	0.58	0.47
Patent Breadth	1.58	1.60	1.47	1.32	1.67
Incrementality	1.71	1.77	1.41	1.05	1.87
Characteristics of the inventor					
Education	23.64	23.87	22.50	21.47	23.80
Experience	4.19	4.70	1.71	1.68	1.73
Tenure	15.87	17.21	9.41	8.05	11.13
Past Publications	9.44	10.36	5.00	4.89	5.13
Past Patent Applications	7.57	7.69	7.00	5.58	8.80
Citations per Publication	7.79	8.71	3.35	1.89	5.21
Networks					
Size of Patent Team	3.06	3.14	2.68	1.95	3.60
Collaboration (Dummy)	0.30	0.30	0.32	0.16	0.53
Compensation mechanisms					
Compensation mechanisms (Dummy)	0.16	0.16	0.15	0.16	0.13
Potential demand pool					
City (Dummy)	0.25	0.21	0.41	0.37	0.47

Table 5.Duration model of labour mobility for European academic inventors

		1	2	3	4	5	6	7	8	9
Technology	Instruments (0/1)	-0.411	-0.472	-0.477	-0.416	-0.369	-0.063	0.018	0.055	0.049
Fixed Effects		[0.77]	[0.87]	[0.85]	[0.76]	[0.65]	[0.10]	[0.03]	[0.08]	[0.07]
	Chem/Pharm (0/1)	-0.169	-0.121	-0.152	-0.074	-0.048	0.696	0.69	0.696	0.694
		[0.35]	[0.24]	[0.30]	[0.15]	[0.09]	[1.05]	[1.05]	[1.04]	[1.11]
	Proc Eng (0/1)	-0.135	-0.065	-0.038	0.062	0.058	1.226	1.225	1.265	1.252
		[0.25]	[0.12]	[0.06]	[0.11]	[0.09]	[1.55]	[1.58]	[1.58]	[1.71]*
	Mech Eng (0/1)	-0.709	-0.704	-0.585	-0.788	-0.44	0.534	0.448	0.447	0.471
		[0.88]	[0.86]	[0.70]	[0.90]	[0.49]	[0.53]	[0.44]	[0.44]	[0.48]
Country	Germany (0/1)		1.117	1.251	1.197	1.348	2.822	2.755	2.721	2.731
Fixed Effects			[2.07]**	[2.03]**	[1.99]**	[2.19]**	[2.56]**	[2.52]**	[2.48]**	[3.19]***
	Netherlands (0/1)		0.887	0.987	1.049	1.02	2.989	2.942	2.873	2.895
			[1.51]	[1.56]	[1.63]	[1.36]	[2.39]**	[2.36]**	[2.29]**	[3.08]***
	UK (0/1)		0.611	0.542	0.492	0.375	2.047	1.983	1.944	1.968
			[1.11]	[0.89]	[0.84]	[0.61]	[1.95]*	[1.90]*	[1.86]*	[2.36]**
Patent Value	Expected Patent value			0.088	0.103	0.142	0.26	0.259	0.252	0.251
				[0.90]	[1.09]	[1.37]	[2.56]**	[2.64]***	[2.71]***	[2.15]**
	Licensed (0/1)			0.457	0.484	0.451	0.877	0.931	0.941	0.933
				[1.13]	[1.17]	[1.05]	[1.49]	[1.63]	[1.74]*	[1.78]*
Networks	Size of patent team				-0.258	-0.238	-0.031	-0.041	-0.053	-0.052
					[1.63]	[1.60]	[0.15]	[0.21]	[0.27]	[0.31]
	Co-ownership				0.181	0.239	-0.689	-0.754	-0.795	-0.838
					[0.29]	[0.39]	[0.68]	[0.75]	[0.79]	[0.84]
	Collaboration (0/1)				0.547	0.513	1.627	1.549	1.526	1.524
					[1.12]	[1.05]	[2.35]**	[2.21]**	[2.20]**	[2.36]**
Knowledge	Cumulativeness (0/1)					0.487	1.034	0.999	0.999	1.008
Characteristics						[1.28]	[1.78]*	[1.75]*	[1.77]*	[2.13]**
	Patent Breadth					-0.119	0.032	-0.022	-0.022	-0.029
						[0.63]	[0.14]	[0.08]	[0.08]	[0.11]
	Incrementality					-0.107	-0.038	-0.039	-0.036	-0.036
						[0.73]	[0.26]	[0.26]	[0.24]	[0.32]
Inventor	Past Patents applications						-0.034	-0.034	-0.035	-0.034
Background							[1.15]	[1.20]	[1.23]	[1.44]
	Gender (0/1)						-0.628	-0.459	-0.464	-0.468
							[0.62]	[0.42]	[0.41]	[0.48]
	Education (yrs)						-0.098	-0.092	-0.089	-0.091
							[1.75]*	[1.69]*	[1.65]*	[1.65]*
	PhD graduated (0/1)						-0.532	-0.571	-0.579	-0.594
							[0.94]	[1.00]	[1.01]	[0.97]
	Experience (yrs)						-0.251	-0.24	-0.237	-0.238
							[2.52]**	[2.34]**	[2.39]**	[3.30]***
	Tenure (yrs)						-0.156	-0.15	-0.15	-0.151
							[3.64]***	[3.58]***	[3.60]***	[4.43]***
	Mobility Before (0/1)						-0.901	-0.856	-0.881	-0.891
							[1.70]*	[1.60]	[1.58]	[1.72]*
	Publications (Stock)						0.01	0.005	0.001	0.001
							[0.29]	[0.14]	[0.03]	[0.02]
	Citations (Stock)						-0.004	-0.003	-0.003	-0.003
							[1.16]	[1.04]	[0.97]	[1.19]
Potential	City (0/1)							-0.327	-0.328	-0.335
Demand								[0.64]	[0.65]	[0.70]

Retention Strategy	Compensation (0/1)								-0.218	-0.229
									[0.33]	[0.39]
	Observations	1348	1348	1348	1348	1348	1348	1348	1348	1348
	Number of Inventor Id	198	198	198	198	198	198	198	198	198
	LL	-141.76	-139.17	-137.98	-135.86	-134.07	-102.2	-101.97	-101.9	-102.05
	Chi2	32.28***	37.55***	37.78***	38.35***	45.63***	175.48***	176.57***	183.66***	72.74***
	ρ									5.06E-07
	Chi2-ρ=0									0.000

Note: Robust z-statistics (***) denotes 1% significance level, (**) denotes 5% significance level and (*) denotes 10% significance level. The baseline hazard function, approximated by a set of time dummy variables, was always highly significant. All standard errors clustered according inventor's ID in order to control for within inventor correlation.

Table 6.Occupational Choice model for European academic inventors

		Pooled	business	pro
Technology	Instruments (0/1)	0.104	-0.14	-0.089
Fixed Effects		[0.17]	[0.16]	[0.09]
	Chem/Pharm (0/1)	0.688	0.048	0.757
		[1.17]	[0.06]	[0.84]
	Eng (0/1)	1.071	1.053	0.543
		[1.53]	[1.22]	[0.54]
Country	Germany (0/1)	2.134	3.184	0.569
Fixed Effects		[2.49]**	[1.61]	[0.58]
	Netherlands (0/1)	2.656	4.632	0.831
		[2.52]**	[1.94]*	[0.80]
	UK (0/1)	1.656	2.505	1.084
		[1.90]*	[1.23]	[1.47]
Paten Value	Expected Patent value	0.263	0.305	0.191
		[2.77]***	[1.65]*	[1.46]
	Licensed (0/1)	0.826	1.332	0.408
		[1.66]*	[1.80]*	[0.36]
Network	Size of Patent team	-0.057	-0.626	0.323
		[0.30]	[2.55]**	[1.35]
	Collaboration (0/1)	1.439	1.385	1.714
		[2.19]**	[0.99]	[2.50]**
Knowledge	Cumulativeness (0/1)	0.793	0.819	-0.025
Characteristics		[1.66]*	[1.27]	[0.04]
	Patent breadth	-0.036	-0.535	0.053
		[0.15]	[1.72]*	[0.24]
	Incrementality	-0.126	-0.134	-0.058
		[1.00]	[1.10]	[0.28]
Inventor	Education	-0.083	-0.2	-0.002
Background		[1.69]*	[1.44]	[0.04]
	PhD graduated (0/1)	-0.739	-1.233	0.399
		[1.43]	[1.36]	[0.39]
	Experience	-0.228	-0.298	-0.167
		[2.75]***	[2.36]**	[1.50]
	Tenure	-0.149	-0.212	-0.09
		[3.61]***	[2.38]**	[2.48]**
	Moved before (0/1)	-0.701	-0.477	-0.71
		[1.42]	[0.61]	[0.88]
	Publications (stock)	0.006	0.023	-0.067
		[0.17]	[0.41]	[1.25]
	Citations (stock)	-0.003	-0.006	0.002
		[0.99]	[1.32]	[0.67]
Potential	City (0/1)	-0.239	0.006	-0.932
Demand		[0.49]	[0.01]	[1.21]
Retention	Compensation (0/1)	-0.017	-0.016	-0.176
Strategy		[0.03]	[0.01]	[0.24]
	Observations	1348	1348	1348
	LL	-103.69	-51.84	-59.96
	Chi2	145.73	203.76	206.1
	P-value	0.00	0.00	0.00

Note: Robust z-statistics (***) denotes 1% significance level, (**) denotes 5% significance level and (*) denotes 10% significance level. The baseline hazard function, approximated by a set of time dummy variables, was always highly significant. All standard errors clustered according inventor's ID in order to control for within inventor correlation.

Figure 1.Inventor's Baseline Hazard functions

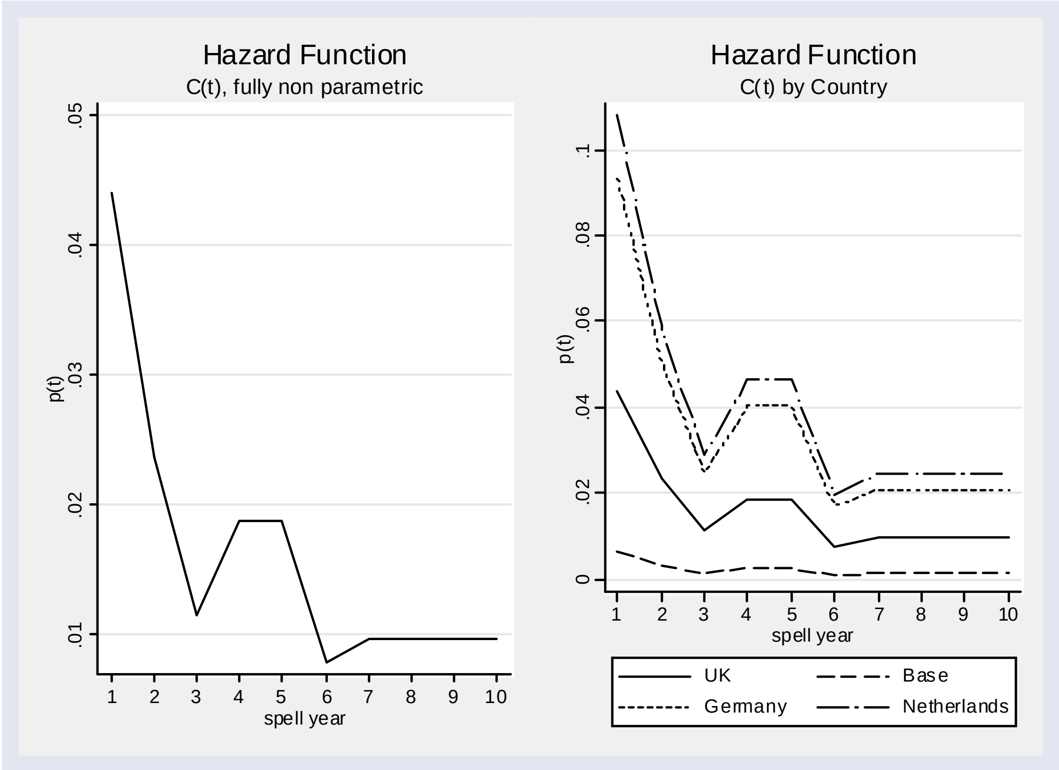

Figure 2.Inventor's Baseline Hazard functions by inventor's characteristics and expected patent value